Essays on Development and Applied Microeconomics

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Except where otherwise indicated, this thesis is my own original work.

Syed Abul Hasan

6 February 2014

To my son, Tamjeed.

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Abstract

This thesis comprises three empirical chapters, which are self-contained but all related to household food consumption in Bangladesh.

Chapter 2 examines the Engel curve for major expenditure categories and presents estimates of equivalence scales for Bangladesh. We compare Engel curves estimated by semi-parametric techniques to those arising from models based on consumer theory. Our analysis supports the argument for a quadratic food Engel curve for developing countries. Knowledge about the correct specification of Engel curves has important implications for modelling household responses to negative income shocks.

Chapter 3 studies the effect of a sharp rice price increase on welfare and poverty in Bangladesh. We employ the household expenditure information to estimate the welfare loss induced by the price increase. Our findings suggest that we underestimate the proportionate welfare loss for rice producing households, and overestimate proportionate welfare loss of households who do not produce rice if we ignore indirect effects arising from a change in household consumption and production behaviour. Our estimates further support the hypothesis of a quadratic relationship between welfare loss and permanent household income. We also demonstrate that higher rice prices either increase or decrease the poverty head-count ratio, depending on the choice of the poverty line. However, if we consider the per capita income gap as a measure of poverty, we always observe that higher rice prices unambiguously increase poverty.

In Chapter 4 we study the effect of the rice price increase between 2005 and 2010 on household rice consumption in Bangladesh. Using a simple difference-in-difference estimator and household level data, we find a negative effect on the value of non-rice food consumption of net rice buyers compared to self-sufficient households. On the other hand, there is no effect on the value of rice or non-food con-

sumption. In contrast, we find that the higher rice price does not effect the value of rice consumption of rice sellers, but increases the value of other food and non-food consumption.

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Chapter 1

Introduction

"As hunger is cured by food, so ignorance is cured by study."

(Unknown Author)

1.1 Motivation and data

Food is the most important necessity for human life. Yet around one in eight people in the world, most of which are concentrated in developing regions, are not getting enough food on a regular basis to conduct an active life (United Nations, 2013). A shortage of food required to maintain regular physical activity may affect the productivity of labour, which immediately affects individual earnings. Inadequate income restricts household spending on food and creates a vicious cycle of poverty and malnutrition (Agénor and Neanidis, 2011). Studies identify infant and young children as the main victims of food insecurity. Inadequate food consumption does not only affect their health in the short-run, but also their cognitive and non-cognitive development in the long-run (Agénor and Moreno-Dodson, 2006; World Bank, 2012). Such a simple but unfortunate fact motivates extensive research on food consumption, generating some useful policy implications. However, we need to know a lot more to make the world free from hunger and malnutrition. Our study is an attempt to cure the ignorance about food consumption in developing countries by providing empirical evidence based on data from the Bangladesh Household Income and Expenditure Survey (HIES).

1.2 Engel curves and equivalence scales for Bangladesh

The formulation of government policies heavily relies on Engel curves as they provide useful insights into many aspects of consumer behaviour (Deaton and Muellbauer, 1980; Banks, Blundell, and Lewbel, 1997; Blundell, Duncan, and Pendakur, 1998). Past studies on advanced economies, which rely on a semi-parametric specification, typically find a linear relationship between the food expenditure share and income, while empirical evidence for rural Pakistan suggests a quadratic food Engel curve (Bierens and Pott-Buter, 1990; Banks, Blundell, and Lewbel, 1997; Blundell, Duncan, and Pendakur, 1998; Bhalotra and Attfield, 1998). However, consumer theory requires a slightly modified specification for Engel curves compared to those used in earlier studies finding a quadratic food Engel curve (Blundell et al., 1998).

Chapter 2 studies Engel curves for major expenditure categories and estimates equivalence scales for households in Bangladesh with diverse demographic characteristics. Our empirical analysis, using semi-parametric and parametric models, provides evidence for quadratic Engel curves for major expenditure categories – including food – in Bangladesh. Our study provides additional evidence to support the argument for quadratic food Engel curves in developing countries. We find that, in the case of a negative income shock, accounting for the curvature of Engel curves is important. Otherwise we may underestimate the expenditure variability of low-income households. Our findings may add to an understanding of consumer behaviour in developing countries.

1.3 The impact of a large rice price increase on welfare and poverty in Bangladesh

Recent experience with world food price shocks refocused research on the study of the impact of such an event on low-income agricultural economies (e.g., Ivanic and Martin, 2008; World Bank, 2010). Previous literature on higher food prices and welfare loss is based on household income and only includes the direct effect of such an event (e.g., Deaton, 1989; Ravallion, 1990; Ivanic and Martin, 2008). On the other hand, studies on the relationship between welfare loss and household income rely on transitory rather than permanent income measures, suffer from endogeneity and use a subjective equivalence scale (e.g., Myers, 2006; Mghenyi et al., 2011). Furthermore, studies on poverty ordering/dominance are mostly based on household income, while poverty estimates usually rely on household expenditure, which is a much more robust measure of household welfare (e.g., Mghenyi et al., 2011).

Chapter 3 simulates the effect of a strong rice price increase on welfare and poverty in Bangladesh. Our empirical analysis finds that accounting for behavioural responses in household production and consumption is important when estimating the welfare effect of low-income households. We find a quadratic relationship between welfare loss and permanent household income. Furthermore, the impact of a higher rice price on the poverty head-count ratio depends on the choice of the poverty line. Overall, the results based on household expenditure are more consistent with theory than those obtained by using household income. Our analysis contributes to the literature on welfare effects of higher food prices by improving both the estimate of proportionate welfare loss and the semi-parametric modelling framework. In addition, it contributes to the analysis of poverty in Bangladesh.

1.4 The impact of the 2005-10 rice price increase on rice consumption in Bangladesh

Food price shocks usually hurt low-income countries around the world. Previous literature investigating the impact of higher food prices in 2007-08 on food consumption ignore the effect on the group that is expected to suffer the most – net rice buyer households, as they suffer from a negative income effect while other types of households do not (e.g. Brinkman, de Pee, Sanogo, Subran, and Bloem, 2010; Alem and

Söderbom, 2010).

Against this background, exploiting the advantage of a natural experiment setting, Chapter 4 studies the effect of a rice price increase between 2005 and 2010 on the consumption of net rice buyer and seller households in Bangladesh. Our empirical analysis finds no significant impact on the value of rice or total consumption, but does find a significant negative impact on the value of other food consumption for buyer households. In contrast, we find no significant impact on rice consumption but a positive impact on both other food and non-food consumption for seller households. Our findings may contribute to the formulation of food policies for developing countries. In particular, to protect the poor from an inadequate consumption of food during a food price shock, it recommends a subsidy on low quality rice. Such policies have the potential to place a lower burden on government budget compared to a general food subsidy.

1.5 Thesis organisation and writing style

Here we discuss the organisation of this thesis. Our thesis is a collection of three independent chapters together with an introduction and a conclusion. Therefore, we keep abstracts in each chapter despite the fact that the thesis abstract is a collection of those independent abstracts. In addition, since chapters in this thesis analyse similar issues using the same data, some arguments particularly the importance of such a study for Bangladesh and the data description may appear repetitive.

It seems relevant to clarify one particular writing style followed in this thesis. The use of 'we', though not very common in writing thesis, is pursued throughout the document. The argument for such practice is that it allows recognition of the contribution of others to this thesis, even if it is tiny or non-academic.

Chapter 2

Engel curves and equivalence scales for Bangladesh[1]

Abstract

This Chapter examines the Engel curve for major expenditure categories and presents estimates of equivalence scales for Bangladesh. We compare Engel curves estimated by semi-parametric techniques to those arising from models based on consumer theory. Our analysis supports the argument for a quadratic food Engel curve for developing countries. Knowledge about the correct specification of Engel curves has important implications for modelling household responses to negative income shocks.

JEL-Classification: D11; O21

Keywords: Engel curve; Semi-parametric estimation; Semi-nonparametric estimation; Partial linear model; Equivalence scale; Base independence; Shape invariance.

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2.1 Introduction

Engel curve, which describes how the expenditure on a commodity varies with household income, provides useful insights into many aspects of consumer behaviour. First, Engel curve has important implications for designing tax policies. For example, a quadratic food Engel curve with a higher tax on food items compared to non-food items, implies a proportionately higher tax burden on low-income people. Second, it permits a study of intra-household disparity in the distribution of resources, including the discrimination against women or elderly persons. Third, Engel curve is crucial in estimating the impact of demographic changes on demand. In a growing economy, these estimates assist in forecasting the demand for some important items like food and energy. Fourth, it provides a basis for the estimation of equivalence scales and thereby allows welfare comparisons between households. Engel curve is also useful for poverty estimation as minimum consumption bundles vary with household's demographic characteristics. Finally, it is useful for predicting the change in a country's trade and production pattern. As a result, formulation of government policy heavily relies on Engel curves (Deaton and Muellbauer, 1980; Banks, Blundell, and Lewbel, 1997; Blundell, Duncan, and Pendakur, 1998).

For a number of reasons, appropriate specifications of Engel curves are particularly important for Bangladesh where a significant proportion of households live on subsistence income (Bangladesh Government, 2007, 2012b). First, the government is expanding the coverage of general sales tax (GST) on food and other necessities (Bangladesh Government, 2012a).[2] Assessment of welfare impact of such an event depends on the assumed shape of Engel curves. Second, official poverty estimates in Bangladesh ignore the use of equivalence scales (Bangladesh Government, 2012b). Incorporating equivalence scales in poverty estimates would make those more appropriate for welfare comparisons. Again, estimation of equivalence scales relies on the shape of Engel curves. Third, like other agrarian economies, household income

[2]GST is known as the Value Added Tax (VAT) in Bangladesh.

is volatile in Bangladesh (Khandker, 2009). Any assessment of the effect of income shocks differs between a linear and a quadratic Engel curve. Therefore, an incorrect specification of Engel curves would not only limit its usefulness in Bangladesh but would also generate misleading outcomes.

Empirical studies based on household data of advanced economies find a combination of linear and quadratic Engel curves for different expenditure categories (Bierens and Pott-Buter, 1990; Banks et al., 1997; Blundell et al., 1998). While these studies typically find a linear relationship between share of food expenditure and income, empirical evidence for rural Pakistan suggests a quadratic food Engel curve (Bhalotra and Attfield, 1998). However, as provided in Blundell et al. (1998), restriction from theory asks for a slightly modified semi-parametric specification for Engel curves compared to the one used in Bhalotra and Attfield (1998).

Against this background, this Chapter studies Engel curves for major expenditure categories in Bangladesh with particular attention to specification issues. In our analysis we use semi-parametric partial linear models to avoid assumptions about the functional form of Engel curves. We also include demographic characteristics in our models using a flexible specification that is consistent with consumer theory. Furthermore, for Bangladesh, we estimate equivalence scales for households with differing demographic characteristics.

In our empirical analysis, we semi-parametrically estimate the Engel curves and simultaneously identify the equivalence scales from our data. Our empirical analysis provides evidence for quadratic Engel curves for major expenditure categories – including food – in Bangladesh. Using household expenditure, adjusted by the estimated equivalence scales, we finally estimate parametric models. As we find evidence of endogeneity of household expenditure in our models, we employ the control function approach to estimate our final models.

Addressing the restrictions imposed by consumer theory on the functional form of the Engel curve and using a different dataset, our study reinvestigates Bhalotra and Attfield (1998) regarding the shape of the food Engel curve for developing countries. Our study provides additional evidence to the argument put forward by Bhalotra and Attfield (1998) – quadratic food Engel curves are a feature of development status. Failing to account for the curvature of Engel curves underestimates the expenditure variability of low-income households who suffer from a negative income shock. Such findings may add to an understanding of consumer behaviour in developing countries and provide valuable input to the formulation of policies.

We organise the Chapter as follows. In Section 2.2, we discuss the literature on the semi-parametric analysis of Engel curves, paying particular attention to developing countries. We also discuss the method used to incorporate demographics into the Engel curve model. A brief discussion of the data is presented in Section 2.3. Section 2.4 deals with methodological issues. The main model is explained in Section 2.5. We discuss the results in Section 2.6. Section 2.7 concludes.

2.2 Semi-parametric analysis and Engel curves

2.2.1 Low-income households and food Engel curve

Motivated by Working (1943), who also finds non-linearities in food expenditure at low income, Bhalotra and Attfield (1998) argue that the food Engel curve is quadratic in developing countries which are characterised by a large proportion of low-income households. In such countries, at low income/expenditure levels, expenditure share on food may either remain constant or decrease more slowly as household income increases.

Grigg (1994), in a slightly different context, discusses reasons which may result in an increasing share of food expenditure in developing countries. First, low-income households, being incapable of meeting their nutritional requirements, usually spend almost all additional income on food when income goes up. Second, urban households, who usually have higher per capita income, depend on purchased food while rural households depend on relatively cheaper farm food.[3] This may imply that the expenditure share of food increases with income. Third, with increasing income, consumers may shift from cheap staples to costly food items like eggs, milk, fish and meat. Altogether, it appears likely that the food Engel curve can be quadratic in developing countries.

2.2.2 Incorporating demographic characteristics in Engel curves

Blundell et al. (1998) show that demographic characteristics impose strong restrictions if they enter linearly in a non-linear Engel curve. Specifically, the linearity of household composition implies that if one good assumes the shape of Working-Leser, then all goods need to be Working-Leser. The study also argues that in a non-linear budget share Engel curve, allowing for flexible shapes over categories requires household expenditures to be adjusted with equivalence scales.[4] Blundell et al. (1998) propose a method to rescale household expenditures through independent of base (IB) equivalence scales. Examples of similar application include Gozalo (1997) and Pendakur (1999). These techniques are however, suitable for analysis with a limited number of household categories.[5]

The argument in Blundell et al. (1998) for scaling household expenditures in the partial linear model (PLM) provides an incentive to reinvestigate the argument for quadratic food Engel curve for developing countries. A procedure for estimating equivalence scales with a larger variation in household types is proposed in Yatchew, Sun, and Deri (2003). The technique is particularly suitable for developing countries, which usually exhibit a large variation in household size and composition.

[3]Food prices are typically low in rural areas where food is usually less processed and involves lower marketing costs. In addition, a significant proportion of rural food consumption is self-produced for which the recorded price is typically low.

[4]An equivalence scale gives the proportion of expenditure or income a household (with a particular demographic composition) is required to achieve the same welfare level as the reference household (Breunig and Cobb-Clark, 2005). Equivalence scales are known as base independent if they do not vary with the utility level (Pendakur, 1999).

[5]We define household categories by the adult-children combination of the household.

2.3 Data

2.3.1 The Household Income and Expenditure Survey

The study utilises data from the 2010 round of Bangladesh Household Income and Expenditure Survey (HIES) – a repeated cross-sectional household survey. The HIES is conducted every 3-5 years and is designed to provide detailed information on household composition, income, consumption and other geographical and socioeconomic variables. Households in that survey are selected using a two-stage stratified random sampling approach. Total number of households in HIES 2010 is 12,240. We use the 2010 wave of HIES as it is characterised by a larger number of households and an extensive use of information and communication technology aimed at reducing measurement errors, compared to the earlier waves (Bangladesh Government, 2012b).

We estimate Engel curves dividing household expenditure into six major categories - 1) food, 2) clothing, footwear and cosmetics, 3) transport, 4) education, 5) medical and 6) other.[6]

2.3.2 Descriptive statistics

Use of household income in our models results in dropping 380 observations with missing income. To allow for sufficient observations for each demographic group, we also drop 1,297 households. Excluded households either include more than four adults or more than four children. Furthermore, we trim 2.5% of the data at the top and bottom of household expenditure, which excludes 528 observations.[7] This is because in non-parametric analysis, estimates perform poorly at both ends of the distribution as the lack of observations increases the variance and makes the confidence band wider (Cameron and Trivedi, 2005). Our final dataset thus includes

[6]The *Other* category includes all items except those that are in the previous five groups. However, several items belonging to a lumpy non-consumption category, like Hajj (pilgrimage) expenditure, are excluded from our analysis.

[7]Our equivalence scales are slightly modified with the use of all observation. However, our conclusions are insensitive to the trimming of data.

10,035 observations. Based on size and composition, each household category has a reasonable number of observations in our final dataset (Table 2.1).

Table 2.1: Family composition

Number of adults	Number of kids 0	1	2	3	4	Total
1	115	193	248	156	53	765
2	723	1,515	1,998	1,173	468	5,877
3	368	622	713	413	183	2,299
4	181	331	327	172	83	1,094
Total	1,387	2,661	3,286	1,914	787	10,035

Descriptive statistics for our expenditure categories are presented in Table 2.2. The Table shows that the mean expenditure share on food is 61 percent, a high proportion even compared to other developing countries, e.g., 47 percent in South Africa (Yatchew et al., 2000). In addition, we find that food expenditure shares vary substantially over its own quantiles.

Table 2.2: Summary statistics: share of expenditures

	Food	Clothing	Transport	Education	Medical	Other
Mean	0.61	0.07	0.05	0.04	0.03	0.20
SD	0.13	0.03	0.05	0.06	0.05	0.10
Min	0.08	0.00	0.00	0.00	0.00	0.00
Max	1.00	0.40	0.81	0.63	0.62	0.81
Percentiles of expenditure shares						
01	0.27	0.02	0.00	0.00	0.00	0.06
05	0.36	0.03	0.00	0.00	0.00	0.09
10	0.42	0.04	0.01	0.00	0.00	0.10
25	0.52	0.05	0.02	0.00	0.01	0.13
50	0.62	0.07	0.04	0.01	0.02	0.18
75	0.70	0.09	0.07	0.06	0.04	0.24
90	0.76	0.11	0.10	0.11	0.08	0.32
95	0.79	0.13	0.14	0.15	0.12	0.39
99	0.84	0.17	0.25	0.28	0.24	0.54
N	10,035	10,035	10,035	10,035	10,035	10,035

Table 2.3 presents means of the dependent variables at different quintiles of total expenditure. It conveniently shows a rapid reduction in food share with increase in

expenditure. Interestingly, the pattern is not very clear for the rest of the categories.

Table 2.3: Means of expenditure shares at different income quintiles

	Quintile-1	Quintile-2	Quintile-3	Quintile-4	Quintile-5
Food	0.66	0.65	0.63	0.59	0.50
Clothing	0.07	0.07	0.07	0.07	0.06
Transport	0.04	0.04	0.05	0.06	0.07
Education	0.01	0.02	0.03	0.05	0.08
Medical	0.03	0.03	0.03	0.04	0.04
Other	0.18	0.18	0.18	0.20	0.25

We present means and standard deviations of independent variables in Table 2.4. Our data shows a high variability of household income compared to household expenditure. This may indicate a relatively higher likelihood for household income to suffer from measurement error.

2.4 Empirical strategy

Two modelling practices guide our selection of explanatory variables. First, due to a likely measurement error in (total) household income, we model Engel curves on (total) household expenditure.[8] Second, like Banks et al. (1997) and Bhalotra and Attfield (1998) we model expenditure shares on the logarithm of household expenditure (log expenditure herein), as such models provide a better fit.

Non-parametric techniques assist in avoiding the specification error. However, data requirements combined with the practical size of surveys, usually force researchers to use semi-parametric (SP) models.[9] SP models may also confirm a particular parametric specification (Breunig and McKibbin, 2012). One particular type of SP model – the partial linear model (PLM) – is employed when there is a strong rationale for certain regressors to enter the model linearly (Blundell and Duncan, 1998).

[8] As Engel and Kneip (1996) point out, in surveys, household income data and therefore household disposable income measures are far from perfect. Measurement error is severe, particularly in agrarian economies (Bhalotra and Attfield, 1998).

[9] An SP model allows some independent variables to enter parametrically into the model, while others enter non-parametrically.

We choose a PLM in which scaled household expenditure enters non-parametrically, while all other variables enter linearly.

Table 2.4: Summary statistics: independent variables

	Mean	SD
Household finances		
Household expenditure	9,454	5,079
Household income	10,760	18,213
Per capita expenditure	2,404	1,411
Per capita income	2,812	4,938
Demographics		
Household head's age	44.62	13.52
Family size	4.18	1.34
Number of adults in the household	2.37	0.78
Number of kids in the household	1.81	1.13
Education		
Household head has no education	0.53	0.50
Household head's spouse has no education	0.53	0.50
Household head has primary education	0.16	0.36
Household head's spouse has primary education	0.17	0.37
Household head has secondary education	0.22	0.41
Household head's spouse has secondary education	0.26	0.44
Household head has higher secondary education	0.07	0.26
Household head's spouse has higher secondary education	0.04	0.19
Household head has graduate degree	0.02	0.14
Household head's spouse has graduate degree	0.01	0.08
Employment		
Proportion of working men	0.27	0.16
Proportion of working women	0.04	0.12
Other		
Urban	0.36	0.48
Lean season	0.17	0.37
Observations	10,035	

Note: 1. We also use information on regions and land ownership – variables closely related to the economic status of the household.
2. Variables in education, work and other categories are dummy variables and indicate their proportion in the sample.

For our non-parametric estimation, we prefer the local linear regression using the Kernel method. The choice of local linear regression is due to its performance at the boundary as well as for its consistency and optimal conversion rate (Yatchew, 2003). In such models, selections of appropriate bandwidths are important as results are sensitive to the choice of bandwidth (Yatchew, 1998). A high bandwidth leads to a large bias with a small variance, while a small bandwidth generates a large variance with a small bias. Both cases lead to a higher residual sum of squares and thus a higher mean squared error (MSE). One criterion for choosing an optimal bandwidth is to minimise the mean integrated squared error (MISE), which is the integrated version of MSE. In our SP models, optimal bandwidths are based on the cross-validation (CV) approach.[10]

Engel curves, when modelled on household expenditure, may suffer from endogeneity, first noted in Summers (1957). Specifically, household expenditure can be endogenous if households decide it jointly with expenditure on each category.[11] For the parametric case, Liviatan (1961) uses household income as an instrument for household expenditure to address such endogeneity. For the semi-parametric case, Blundell et al. (1998) suggest running a parametric regression of the endogenous variable(s) on a set of instruments and adding the residuals from this regression as an additional covariate in the SP model. Such procedures generate consistent estimates while significance of the residuals may indicate the presence of endogeneity. Newey, Powell, and Vella (1999), on the other hand, suggest generating residuals through the non-parametric regression. We follow the latter methodology.

Engel curves, in which expenditure shares are plotted against income/expenditure, are called shape invariant if the shapes are identical (though may shift horizontally or vertically) for different demographic groups. Base independent equivalence scales provide shape invariant Engel curves.[12] We assume base independence to incorporate demographics in the Engel curves, as recommended in Blundell et al. (1998) and Blundell, Chen, and Kristensen (2007).

In order to model Engel curves with larger variations in family composition, we employ the following functional form for the equivalence scales, proposed in

[10]The SP model estimation technique is described in Appendix-2.A.

[11]In addition, unobserved preference heterogeneity, included in errors in Engel curve models, may also cause household expenditure endogenous.

[12]The reverse is usually but not always true (Pendakur, 1999). Here, we use both synonymously.

Yatchew et al. (2003)[13]

$$\Delta = (A + \beta_2 K)^{\beta_1}, \tag{2.1}$$

where, Δ is the equivalence scale, A is the number of adults and K is the number of children in the household. The parameter β_1 captures the economy of scale in household expenditure while β_2 captures the impact of children on household expenditure. A value of 1 for β_1 indicates that doubling both the number of adults and children in the household requires expenditure to be doubled for maintaining the same level of welfare. Similarly, a value of 1 for β_2 indicates that, to maintain the same level of welfare, children require exactly the same amount of resources as adults. The proposed functional form generates equivalence scales which are monotone in both A and K. Our equivalence scales are based on entire expenditure categories, which is a requirement for consistent estimates, but rare to find in earlier studies. We estimate the model through a grid search for both the parameters over the range from 0.1 to 1.0.

Finally, we perform a specification test following Hardle and Mammen (1993) to verify whether the SP model can be approximated by a quadratic fit. Unfortunately, when expenditure shares are modelled on the log of household expenditure, it is not possible to identify the equivalence scale and its elasticity separately (Blackorby and Donaldson, 1993). Therefore, we are eventually making three assumptions in our model – non-linearity of Engel curves, base independence of equivalence scales and appropriate functional form for the equivalence scales. Failure to satisfy any of these assumptions may result in an unsatisfactory test result.

2.5 Model and estimation

To illustrate our model we start with two households A and B, with the former being the reference household. Denoting p as the vector of prices common to both

[13]Our final dataset includes a total of 20 different types of households.

households and u as some arbitrary level of utility, we may write

$$E^A(p,u) = \frac{E^B(p,u)}{\Delta^B(p,u)}, \tag{2.2}$$

where $E^h(p,u)$ is the expenditure function giving household $h \in \{A, B\}$ a utility u at prices p. The equivalence scale $\Delta^B(p,u)$ scales household B's expenditure such that the scaled expenditure gives A the same utility as B (equivalent expenditure).

The base independence assumption, which assumes that the equivalence scale does not depend on the utility level, implies $\Delta^B(p,u) = \Delta^B(p)$. Therefore, we may express (2.2) with the dual indirect utility function as

$$E^B(p, V(p,y)) = \Delta^B(p) E^A(p, V(p,y)), \tag{2.3}$$

where V represents the indirect utility function and y represents household income. Equation (2.3) is equivalent to

$$V^B(p,y) = V^A(p,y)/\Delta^B(p). \tag{2.4}$$

Since the expenditure functions are homogeneous of degree one in prices, the equivalence scale function must be homogeneous of degree zero in prices. Thus Blackorby and Donaldson (1993) express (2.4) as

$$V^B(p,y) = V^A\left(p, \frac{y}{\Delta^B(p)}\right). \tag{2.5}$$

Pendakur (1999) uses Roy's identity to derive the Marshallian demand equations

$$x_i^B(p,y) = x_i^A\left(p, \frac{y}{\Delta^B(p)}\right)\Delta^B(p) + \frac{y}{\Delta^B(p)}\frac{\partial \Delta^B(p)}{\partial p_i}, \tag{2.6}$$

where x_i^h represents total expenditure on goods i for household h.

Multiplying (2.6) with p_i/y gives us the Marshallian expenditure share equations

$$w_i^B(p,y) = w_i^A\left(p, \frac{y}{\Delta^B(p)}\right) + \eta_i^B(p), \tag{2.7}$$

where w_i^h gives the expenditure share of commodity i for household h, and $\eta_i^B(p)$ is the elasticity of the equivalence scale for household B with respect to the price of good i.

If prices are constant, as in our cross-sectional data, the model reduces to

$$w_i^B(y) = w_i^A\left(\frac{y}{\Delta^B}\right). \tag{2.8}$$

We also include some non-demographic variables in our model like regional, urban and work dummies as well as household head and his/her partner's education. Expressing expenditure share of a category as a function of log expenditure and generalisation for more household categories gives our model as

$$w_i = F(logy - Z\delta) + V\lambda_i + v \tag{2.9}$$

where F is an unknown function, $\delta = log\Delta$, Z is a vector of indicator variables for demographic composition, V includes Z and a set of non-demographic variables enters linearly in the model, λ_i is a vector of parameters and the error term $v \sim NID(0,\sigma^2)$.

Substituting the equivalence scale Δ from (2.1) gives our final model,

$$w_i = F\left(logy - \beta_1 log(A + \beta_2 K)\right) + V\lambda_i + v. \tag{2.10}$$

2.6 Results and discussion

As a diagnostic check for the shape of the Engel curves, we first perform quantile regressions for all the expenditure categories.[14] Our plots of conditional quantile estimate of the coefficients for log expenditure in Figure 2.1 show that though the direction of the impact is the same across quantiles of the dependent variables, there is a systematic pattern in the variation of the coefficients, indicating towards non-linearity of Engel curves.

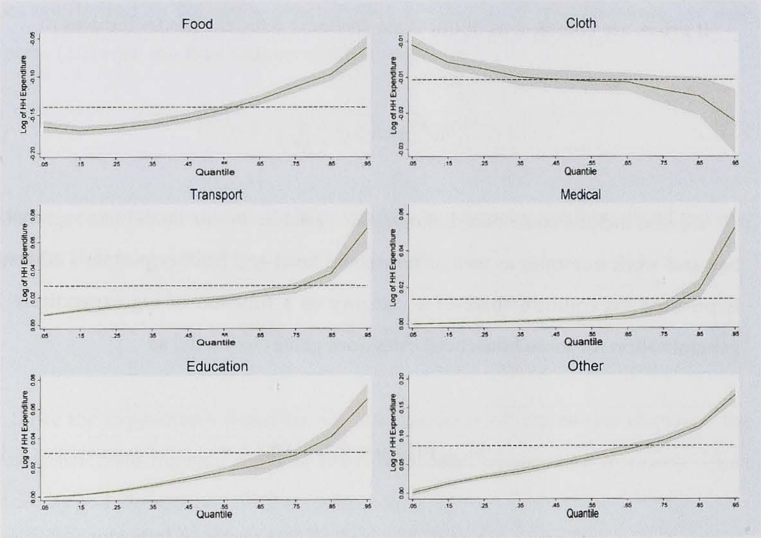


Figure 2.1: Plot of coefficients at different quantiles

We estimate our model using the SP regression technique with control for the endogeneity of (total) household expenditure. In doing so, we also identify the equivalence scales based on all six expenditure groups. Specifically, we choose values for β_1 and β_2 that minimise the sum of squared residuals (SSR), aggregated over all six

[14]As mentioned in Koenker and Hallock (2001) and Knight and Ackerly (2002), quantile regressions are useful for diagnostic checks with heteroscedastic error terms and outliers in the dependent variable.

groups.[15] With a value of 0.74 for β_1 and 0.17 for β_2, our model indicates a substantial scope for the economies of scale and a low impact of children on household expenditure. Given the high expenditure share of food, which is a rival good, the estimate for the economies of scale in family expenditure seems sensible. In addition, lower food requirements for children, together with minimal non-food expenditures at low income, jointly explains the lower value for β_2.[16] Using the functional form in equation (2.1), our estimated equivalence scales are presented in Table 2.5.

Table 2.5: Estimated equivalence scales

Number of adults	Number of kids 0	1	2	3	4
1	1.00	1.12	1.24	1.36	1.47
2	1.67	1.77	1.88	1.98	2.07
3	2.25	2.35	2.44	2.53	2.62
4	2.79	2.88	2.96	3.05	3.13

One implication of the base independence assumption is that the semi-parametrically estimated Engel curves for households with different family compositions would be of similar shape. Graphically, this indeed holds for food, as presented in Figure 2.2. The shapes of Engel curves for our selected demographic groups also look similar for both clothing and the other expenditure category. For some categories, Engel curves have different shapes, which might be a consequence of a low number of observations. However, expenditure categories that appear to be shape invariant, like food, clothing and other expenditures, altogether account for around 90% of total household expenditure.

To investigate the shape of Engel curves, we present the semi-parametric fit in Figure 2.3.[17] For each category, we compare the shapes arising from the SP model

[15] In our analysis, the SSR has a global minimum for each of the parameters, given the value of the other.

[16] The equivalence scale parameters are similar even if we consider only one category – food or a subgroup like food and cloth. This highlights that most variations in the equivalence scales come from food expenditure.

[17] We thank Vincenzo Verardi and Nicolas Debarsy of University of Namur, Belgium, for sharing their Stata codes for semi-parametric model estimation, see Verardi and Debarsy (2011).

to a quadratic fit. The figure shows that for some categories including food, the quadratic model fits the data relatively well.

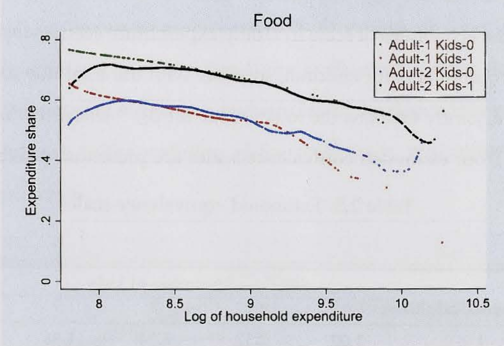


Figure 2.2: Semi-parametric estimate of food share for different family types

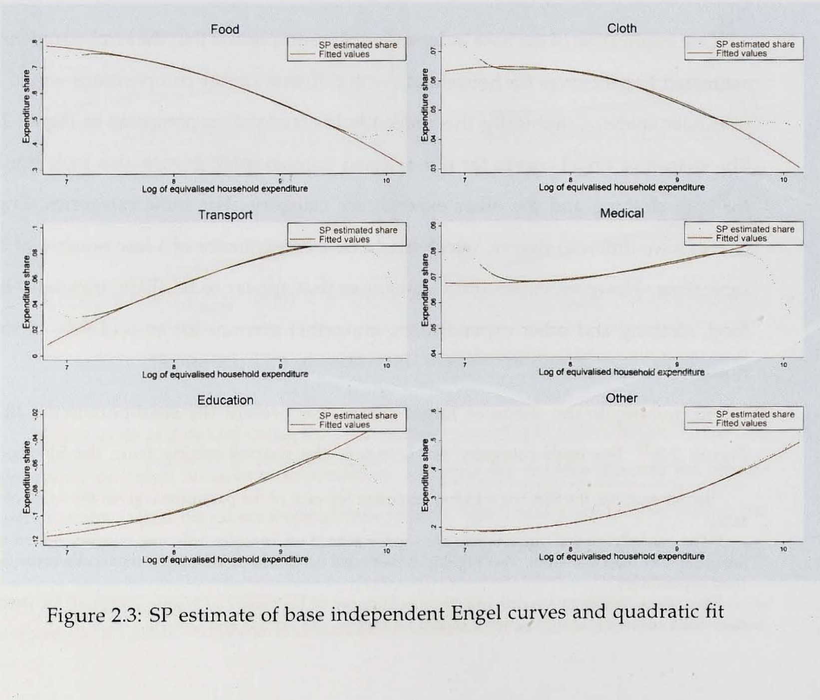


Figure 2.3: SP estimate of base independent Engel curves and quadratic fit

We check if the SP fit can be approximated by a parametric adjustment of order two, by conducting a specification test proposed in Hardle and Mammen (1993). When our choice of the level of significance is 10%, we cannot reject the hypothesis that 'the quadratic fit and the non-parametric fit are not different' for food, clothing, medical and other categories. We are also unable to reject the same hypothesis for the transport expenditure share at 5% level of significance. However, we reject the null hypothesis of quadratic fit for education over 1% level of significance (Table 2.6). In addition to the non-linearity of models, a violation of the base independence assumption or a misspecification of the equivalence scale function may also be responsible for such rejections.

Table 2.6: Hardle and Mammen (1993) test results

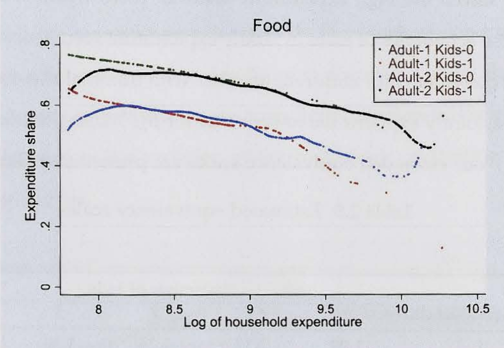
Expenditure shares	p-value
Food	0.24
Clothing	0.12
Transport	0.06
Medical	0.39
Education	0.01
Other	0.89

Note: H_0: The SP fit can be approximated by a quadratic fit.
H_1: A quadratic fit cannot approximate the SP fit.

Next, we fit a parametric model which is quadratic with equivalised expenditure and linear in other covariates. We start with OLS estimates as in a two-stage budgeting system, (total) household expenditure can be exogenous in models of Engel curve. In that process, households first decide income and total expenditure. Next, in the second stage, given total expenditure, they decide expenditure on each category. This particularly seems valid for people with subsistence income, as our case is. Because, at low income, people usually do not have much scope to decide their income based on their expenditure, indicating exogenous household income in the models of Engel curve.[18] In addition, low-income households are forced to spend all income on consumption. Hence, given total expenditure, they decide expenditure on each

[18]This excludes the possibility of reduced income caused by an inadequate expenditure on food.

to a quadratic fit. The figure shows that for some categories including food, the quadratic model fits the data relatively well.



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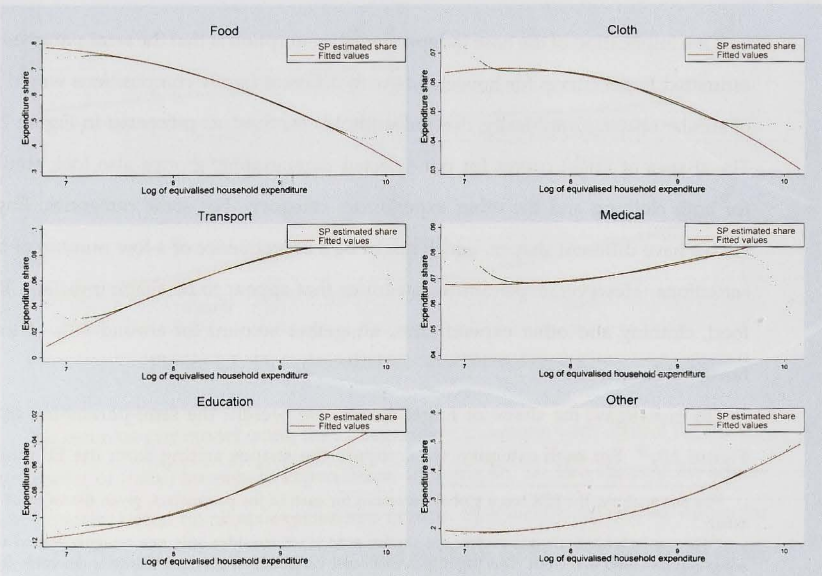

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[18]This excludes the possibility of reduced income caused by an inadequate expenditure on food.

category which also makes household expenditure exogenous in our models. The OLS estimates, presented in Table 2.7, for both the level and the quadratic terms are significant for food, clothing, transport, education and other items at 5% significance level. As is a common case for Engel curves, the adjusted R^2, though reasonable for food, education and other items, is particularly low for medical expenditures.[19]

Table 2.7: OLS estimate of expenditure shares

	Food	Clothing	Transport	Medical	Education	Other
Log of equivalised household expenditure	0.558*** (0.074)	0.056*** (0.018)	0.108*** (0.034)	-0.019 (0.031)	-0.097*** (0.035)	-0.607*** (0.069)
Squared log of equivalised expenditure	-0.040*** (0.004)	-0.004*** (0.001)	-0.005** (0.002)	0.002 (0.002)	0.008*** (0.002)	0.040*** (0.004)
Adjusted R^2	0.38	0.11	0.10	0.04	0.24	0.23
F	228	46	37	12	104	86
N	10,035	10,035	10,035	10,035	10,035	10,035

Note 1: Standard errors in parentheses.
Note 2: * p <0.10, ** p <0.05, *** p <0.01.

It can be argued that the non-linearity of Engel curves may be due to the specification error. In our models, we allow the demographic and non-demographic variables to shift the curve. However, we also restrict the value of the coefficients across heterogeneous groups. This might result in spurious curvature of Engel curves. Nonetheless, we find that for all six expenditure categories, shapes of Engel curves are similar for households across different regions, industries or occupations. Tobit models, applied on categories with a large fraction of missing values, produce similar results.

Now we check if household expenditure is endogeneous in our models as OLS estimates are inconsistent if it is the case while IV estimates are inefficient when it is exogenous. We employ both household income and household landholding size as instruments for that purpose. Our analysis finds evidence for endogenous household expenditure – except education, in Engel curves for all categories we reject

[19]Heteroscedasticity is a common case in the estimation of Engel curves. At higher incomes people are usually more flexible in allocating resources across expenditure categories. In contrast, variability of expenditure is low at low incomes when most resources are allocated to subsistence. Since we find the same for our case, we use robust standard errors.

the exogeneity of log expenditure at 10% level of significance (Table 2.8).

Table 2.8: Exogeneity test: p-values

Expenditure shares	Test of exogeneity
Food	0.000
Clothing	0.000
Transport	0.002
Medical	0.000
Education	0.410
Other	0.000

Note: Wooldridge's (1995) robust score test and a robust regression-based test are reported. If the test statistic is significant, the variables being tested must be treated as endogenous.

Empirical studies on Engel curves like Banks et al. (1997), Blundell et al. (1998), Bhalotra and Attfield (1998) and Blundell et al. (2007) routinely perform IV estimation to deal with the problem of endogeneity and obtain unbiased estimates. In such studies it is common to use household income as an instrument of household expenditure as the former is related to the latter while it has no direct impact on expenditure shares. Similar arguments also hold for household land holding size. Using these two as instruments, IV estimates for our Engel curves are presented in Table 2.9. Surprisingly, only the Engel curve for the clothing expenditure category appears quadratic in our estimate. In all other cases, not only the quadratic term but also the level term appears insignificant (Figure 2.4).

Table 2.9: IV estimate of expenditure shares

	Food	Clothing	Transport	Medical	Education	Other
Log of equivalised household expenditure	0.068	0.320**	-0.619	-0.067	0.225	0.072
	(0.639)	(0.161)	(0.439)	(0.291)	(0.299)	(0.504)
Squared log of equivalised expenditure	-0.013	-0.019**	0.038	0.004	-0.012	0.001
	(0.038)	(0.010)	(0.026)	(0.017)	(0.018)	(0.030)
Adjusted R^2	0.36	0.04	0.04	0.03	0.23	0.20
N	10,035	10,035	10,035	10,035	10,035	10,035

Note 1: Standard errors in parentheses.
Note 2: * p <0.10, ** p <0.05, *** p <0.01.

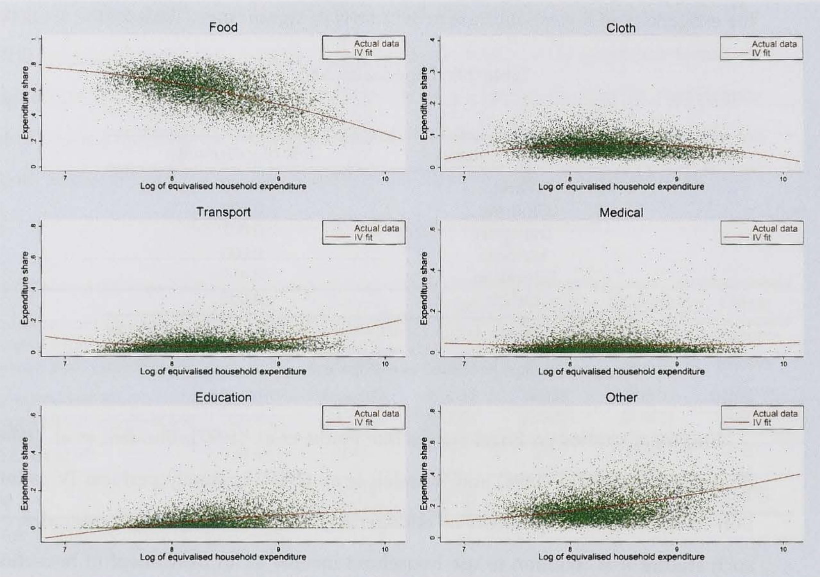

Figure 2.4: Actual data and IV fitted quadratic Engel curves

Such results enable us to confirm the quality of instruments used in our IV estimation. Looking at the first stage regression, we find our instruments strong. However, the high collinearity between the two endogenous variables – log expenditure and its square – might be responsible for inflating the standard error and thus making estimates insignificant. Next, we check if the instruments satisfy the exclusion restriction. A test of over-identifying restrictions cannot reject the null hypothesis that the excluded instruments are valid for all expenditure categories at the 5% level of significance (Table 2.10). However, low p-values for three expenditure categories in the test suggest that at least one of our instruments might not be valid.

We reject both OLS and IV estimates due to unsatisfactory test results and finally employ the control function (CF) approach to control for endogeneity. Compared to IV, the CF approach has an advantage of providing more precise estimates when the endogenous variable enters into the model non-linearly (Wooldridge, 2010). In the CF approach, residuals from the first stage regressions enter as additional covariates in the original model to control for endogeneity. Additionally, significance of the first stage residuals can indicate the endogeneity of the suspected variables. As we have two endogenous variables in our models (log expenditure and its square), including two reduced form residuals produces estimates identical to the IV approach. However, now we can test whether both of the first stage residuals contribute to controlling endogeneity. In case we find either one enough to control endogeneity, estimates would be more efficient in our non-linear setting.

Table 2.10: Overidentifying restrictions test: p-values

Expenditure shares	Test of over-identifying restrictions
Food	0.065
Clothing	0.102
Transport	0.337
Medical	0.057
Education	0.380
Other	0.265

Note: Basmann's (1960) chi-squared tests are reported, as is Wooldridge's (1995) robust score test. A statistically significant test statistic always indicates that the instruments may not be valid.

In selecting better models for each expenditure category, we compare models that include two reduced form residuals against models that only include residuals from the reduced form of level term. Though Akaike information criterion (AIC) marginally supports bigger models for cloth and transport categories, Bayesian Information Criterion (BIC) unambiguously supports the parsimonious models for all six expenditure categories. This reveals that, for all categories, the residual of the reduced form for log expenditure is enough to control for the endogeneity for household expenditure.[20] These parsimonious models provide our final estimates presented in Table 2.11. In these estimates, Engel curves for all the expenditure categories except medical expenses are quadratic. It is therefore consistent with the argu-

[20]Banks et al. (1997) finds the same for the quadratic model.

ment in Bhalotra and Attfield (1998) that developing countries may have a quadratic food Engel curve. Estimated Engel curves with the CF approach are presented in Figure 2.5.

Table 2.11: OLS estimate of expenditure shares-CF approach

	Food	Clothing	Transport	Medical	Education	Other
Log of equivalised household expenditure	0.484^{***} (0.075)	0.088^{***} (0.018)	0.126^{***} (0.035)	-0.042 (0.032)	-0.102^{***} (0.036)	-0.555^{***} (0.071)
Squared log of equivalised expenditure	-0.038^{***} (0.004)	-0.005^{***} (0.001)	-0.006^{***} (0.002)	0.003 (0.002)	0.008^{***} (0.002)	0.038^{***} (0.004)
Residual	0.045^{***} (0.007)	-0.020^{***} (0.002)	-0.011^{***} (0.003)	0.014^{***} (0.003)	0.003 (0.004)	-0.032^{***} (0.006)
Adjusted R^2	0.38	0.13	0.10	0.04	0.24	0.23
F	223	48	36	12	100	84
N	10,035	10,035	10,035	10,035	10,035	10,035

Note 1: Standard errors in parentheses.
Note 2: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

One of the arguments for a quadratic Engel curve is that low-income households spend all additional income on food to meet their nutritional requirements. If this argument is valid, we would expect similar slopes for different food categories. A contrasting argument is that with increase in household expenditure, consumers shift from cheap staples to costly food items. This implies changes in the composition of food consumption to a change in household expenditures.

To evaluate different arguments for a quadratic food Engel curve, we use our earlier framework – semi-parametric PLM, but now include more disaggregated expenditure categories like rice, protein, fruits & vegetables, non-home-made food, otherfood, tobacco, clothing, footwear & cosmetics, transport, education, medical and other expenditure. In our new setting, the value for the economies of scale parameter in the equivalence scale function is 0.57 – lower than the value from our earlier setting, 0.74. However, the impact of children on household expenditure remains the same at 0.17. In our analysis, household expenditure has the opposite impact on the expenditure share of some important food categories like rice and protein. This provides limited support for the first argument but supports the second. As household expenditure increases, expenditure on some food categories like protein, non-home-made food and other food increasingly dominates over expenditure on some other categories including rice and fruits & vegetables, resulting in a quadratic Engel curve. A quadratic food Engel curve may therefore successfully aggregate different types of food expenditures.

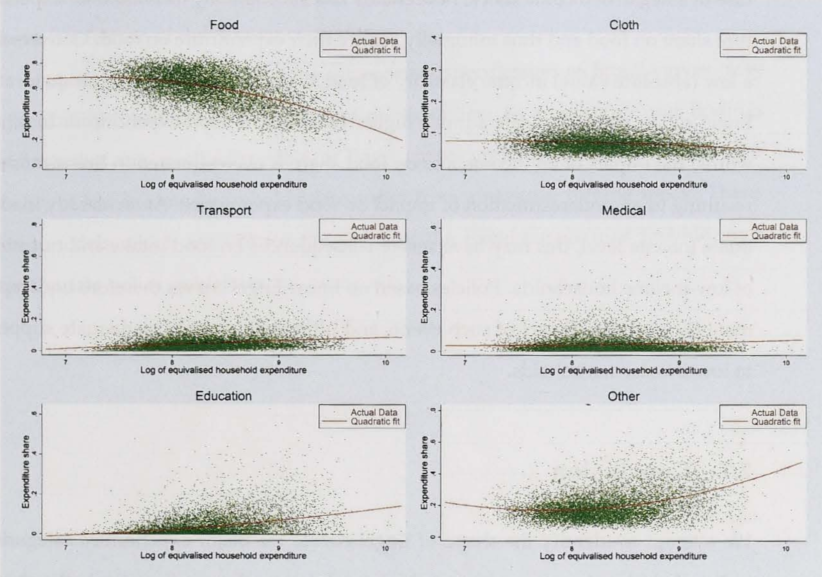

Figure 2.5: Actual data and OLS fitted quadratic Engel curves – CF approach

Income shock and food consumption of low-income households

Earlier, we argue that quadratic Engel curves yield different policy implications. Here we provide an example with the food Engel curve for Bangladesh. We start assuming a negative income shock which is observed by all households in the economy. This allows us to study the impact of such an event on food expenditure of low-income households, say with expenditure equal to the 10th percentile of our equivalised expenditure.[21] The estimated elasticity of food share from the quadratic model for the reference household (single adult with no children) at the sample means of other regressors in the model is -0.17. However, a model linear in household expenditure provides elasticity equal to -0.23.[22]

Now, a high (absolute value) income elasticity of food share implies that, in the case of a negative income shock, households will substantially increase their expenditure share on food and thus minimally reduce their expenditure on food. Conversely, a low (absolute value) income elasticity of food share, as is the case for our quadratic Engel curve, would indicate a much higher reduction in food expenditure. In other words, the impact of an income loss on food share is overestimated in linear models resulting in an underestimation of impact on food expenditure. At an already inadequate income level, this may have severe consequences on food intake and nutrition of low-income households. Policies based on linear Engel curves therefore underestimate the negative impact of such events and ultimately provide inadequate support to low-income households.

2.7 Conclusion

We attempt to identify the shape of Engel curves for major expenditure categories in Bangladesh using recent household data. In particular, we investigate the shape of the food Engel curve for Bangladesh. To determine the shape from the data, we use a semi-parametric model which also takes care of the restrictions imposed by consumer theory on the functional form of the Engel curve.

The Hardle and Mammen test with the semi-parametric specification indicates that Engel curves for most of the expenditure categories may have a quadratic shape.

[21]The official estimate of poverty, which is based on the same data we use, is 31.5 percent in Bangladesh.

[22]In the linear model, even though the equivalence scale is not identified, we use equivalent household expenditure.

Hence we fit parametric models for Engel curve which are quadratic in household expenditure. In such models we utilise the control function approach to control for the endogeneity of household expenditure. Our results also indicate that the food Engel curve for Bangladesh is quadratic. This is different from the Working-Leser type food Engel curves, typically found for developed countries. Our analysis thus provides additional evidence to support the hypothesis that quadratic food Engel curve is a feature of developing countries.

Our analysis, in identifying the appropriate specification of Engel curves, may significantly contribute to the design of public policy. As an example, our findings indicate that mis-specified models for Engel curves underestimate expenditure variability of low-income households who suffer from a negative income shock. Therefore, models which account for the shape of the Engel curves may provide more appropriate policy guidelines.

Appendix 2.A Semi-parametric model estimation

Estimation of semi-parametric models in this Chapter follows Robinson (1988). First, we predict the dependent and all independent variables non-parametrically from log expenditure. Second, for the dependent and all independent variables, we obtain the difference between the actual and predicted value of each variable. Third, we use OLS to estimate the coefficients of independent variables, by regressing the differenced dependent variable on differenced independent variables, which enter parametrically into the model. We use estimated coefficients to estimate the impact of these variables on the dependent variable. Now we subtract these estimated values (impacts) from the dependent variable, so that we are only left with the impact of log expenditure on the dependent variable. Finally, we again run the non-parametric regression of impact free variable on log expenditure.

With $\bar{y}$ representing equivalised expenditure, our SP model is[23]

$$w_i = F(log\bar{y}) + V\lambda_i + v. \tag{2.11}$$

Assuming household expenditure to be uncorrelated with error, the conditional expectation of (2.11) is given by

$$E[w_i|log\bar{y}] = F(log\bar{y}) + E[V|log\bar{y}]\lambda_i. \tag{2.12}$$

Estimates of the conditional moments can be found through non-parametric local linear regression. Subtracting (2.12) from (2.11) gives,

$$w_i - E[w_i|log\bar{y}] = (V - E[V|log\bar{y}])\lambda_i + v. \tag{2.13}$$

The vector λ_i can be estimated by OLS using (2.13). We can use these estimates

[23]This section borrows from Breunig and McKibbin (2012).

along with the estimated conditional moments in (2.12) to find an estimate of $F(log\bar{y})$,

$$\widehat{F(log\bar{y})} = E[\widehat{w_i|log\bar{y}}] - E[\widehat{V|log\bar{y}}]\hat{\lambda}_i. \tag{2.14}$$

In modelling the Engel curve, household expenditure is expected to suffer from endogeneity. To control for endogeneity, we predict the residuals from non-parametric estimation of log expenditure on the log of household income. Then we use those residuals as an additional covariate while estimating equation (2.13) by OLS. Such procedure generates consistent estimates of the covariates while the significance of the residuals may also indicate the presence of endogeneity.

[illegible]

With [illegible]

[illegible] (2.11)

Assuming household expenditure [illegible] the conditional expectation of (2.11) is given by

[illegible] (2.12)

Estimates of the conditional moments can be [illegible] local linear regression. Subtracting (2.12) from (2.11) gives

[illegible] (2.13)

The vector [illegible] can be estimated by OLS using (2.13). [illegible]

[illegible]

Chapter 3

The impact of a large rice price increase on welfare and poverty in Bangladesh[1]

Abstract

This Chapter studies the effect of a sharp rice price increase on welfare and poverty in Bangladesh. We employ household expenditure information to estimate the welfare loss induced by the price increase. Our findings suggest that the proportionate welfare loss is underestimated for rice producing households and overestimated for households who do not produce rice, if we ignore indirect effects of higher price arising from a change in household consumption and production behaviour. Our estimates further support the hypothesis of a quadratic relationship between welfare loss and permanent household income. We also demonstrate that higher rice prices either increase or decrease the poverty head-count ratio, depending on the choice of the poverty line. However, if we consider the per capita income gap as a measure of poverty, we always observe that higher rice prices unambiguously increase poverty.

JEL-Classification: O13, O53, Q12, D12, I32

Keywords: Welfare; Rice Price; semi-parametric Regression; Bangladesh; Poverty.

[1]We thank Robert Breunig, Mathias Sinning and participants of the 2013 Crawford PhD conference in ANU for helpful comments.

3.1 Introduction

Recent experience with world food price shocks brings the spotlight back on the study of such events, especially their impact on low-income agricultural economies. Between January 2007 and April 2008, for example, the price of coarse rice in Bangladesh nearly doubled (World Bank, 2010). Such an event may have a considerable negative impact on the welfare of low income households. Protecting households from the negative consequence of food price increases requires knowledge about the precise impact of price changes on welfare and poverty. At the same time, identifying the most affected income groups requires an investigation of the relationship between welfare loss and income.

Studying the welfare effects of a higher rice price in Bangladesh is important for several reasons. First, the share of rice in total expenditure is very high. Second, the cross price elasticity of rice demand with respect to the price of wheat is very low, indicating little substitutability of wheat for rice (Dorosh and Shahabuddin, 2002).[2] Third, as a net importer of food grains, Bangladesh depends on imported rice for fulfilling its domestic demand (Bangladesh Government, 2012a). The country also depends on the harvest for its food security. Altogether, these may make the country vulnerable to rice price shocks, originating either from international or domestic sources. Furthermore, like many other developing countries, Bangladesh exhibits a large proportion of low income households (Bangladesh Government, 2012b). While the majority of these low income households are net rice buyers, a significant proportion of them are also associated with rice farming. Hence, it is interesting to investigate how a higher rice price affects household welfare in Bangladesh.

The literature on higher food prices and welfare loss suffers from several limitations. First, estimates of welfare loss induced by higher food prices are usually imprecise because most studies (e.g., Deaton, 1989; Ravallion, 1990; Ivanic and Martin, 2008) only consider the first round effect. Ignoring the second round effect results

[2] Wheat constitutes the second largest item in household food expenditure in Bangladesh.

in an imprecise estimate of welfare loss, particularly when the price change is large.[3] Moreover, when estimating welfare losses, most studies (e.g., Mghenyi, Myers, and Jayne, 2011; Myers, 2006) rely on a household income measure which is typically prone to measurement error in household surveys. Second, when studying the relationship between welfare loss and household income, many studies rely on transitory rather than permanent income measures. Semi-parametric models may further suffer from endogeneity (e.g., Mghenyi et al., 2011). In addition, many studies use a subjective scale to convert household income into adult equivalent income. Third, studies on poverty ordering/dominance (e.g., Mghenyi et al., 2011; Chen and Duclos, 2011) are mostly based on household income.[4] However, poverty estimates usually rely on household expenditure which is a much more robust welfare measure than household income (Ravallion, 1992). Hence, the use of household expenditure also seems appropriate for poverty comparisons.

Against this background this Chapter studies the effect of a strong rice price increase on welfare and poverty in Bangladesh using a recent wave of household survey data. When calculating household welfare, our analysis is based on household expenditure instead of household income. We include both the direct effect of a higher rice price, which lowers the entitlement of net rice buyers and increases the entitlement of net rice sellers, as well as the indirect effect arising from the adjustment of households' production and consumption behaviour.[5] Using household expenditure as a proxy for permanent household income, we investigate its relationship to welfare loss.[6] We further address the endogeneity of household expenditure

[3]As the second round effect is much smaller than the first round effect, it is usually ignored when the price change is small.

[4]Poverty ordering/dominance indicates whether, for a particular class of poverty measure (such as head-count ratio or per capita income gap), the poverty level is higher or lower in one distribution compared to another.

[5]The direct effect is also known as the distributional effect or the first round/order effect of a higher rice price. The rice price increase also results in some behavioural responses. In particular, it may reduce rice consumption and increase rice farming. This adjustment is known as the indirect or second round effect.

[6]By permanent household income we refer to the long-run income of the household. The advantage of using household expenditure, compared to household income, as a proxy for permanent household income, is provided in (Meyer and Sullivan, 2012).

in our model by using household non-farm income as an instrument. Finally, we analyse the impact of a higher rice price on consumption based poverty.

Our empirical analysis generates some important findings. First, using an equivalent variation measure of welfare change, we find that accounting for behavioural responses in household production and consumption is important when estimating the welfare effect of low income households. Second, we typically find a quadratic relationship between the welfare loss and permanent household income. Third, a higher rice price may either increase or decrease the poverty head-count ratio, depending on the choice of the poverty line. However, if we consider the per capita income gap as a measure of poverty, we find that poverty increases with a higher rice price. Overall, the results based on household expenditure are more consistent with theory than those obtained by using household income.

This Chapter contributes to the literature on welfare effects of higher food prices in several ways. First, we improve the estimate of proportionate welfare loss by using household expenditure and by capturing the second round impact. Second, when analysing the relationship between welfare loss and household income, we employ a rich semi-parametric modelling framework, which allows us to control for endogeneity and permits the use of household expenditure, equivalised by a semi-parametrically estimated equivalence scale. Third, we contribute to the analysis of poverty in Bangladesh, where we use the idea of poverty dominance in combination with household expenditure in assessing the impact of a higher rice price.

The Chapter is structured as follows. Section 3.2 provides a description of the data. Section 3.3 discusses the estimation of the proportionate welfare loss. Section 3.4 addresses the relationship between welfare loss and household income. The impact of a higher rice price on poverty is discussed in Section 3.5. Section 3.6 concludes.

3.2 Data

We use the 2010 wave of the Bangladesh Household Income and Expenditure Survey (HIES) in our analysis. HIES is a repeated cross-sectional household survey conducted every 3 to 5 years and is designed to generate nationally representative socio-economic information at the household and individual level. Selection of households in the HIES uses a two-stage stratified random sampling approach under the framework of an integrated multi-purpose sample design. HIES includes detailed regional and socio-economic information, including data on household production, income, and consumption. The total number of households in the 2010 round of HIES is 12,240 (Bangladesh Government, 2011a, 2012b).

Repeating the research with the 2005 round of HIES does not affect our main findings qualitatively. We prefer the results obtained from the 2010 wave for two reasons. First, some questions of the survey were modified between 2005 and 2010. Second, the 2010 HIES interviews a larger number of households and makes extensive uses of information and communication technology to reduce errors (Bangladesh Government, 2011a, 2012b).

The data shows that household expenditure shares of rice range from 11 to 20% in urban and from 18 to 29% in rural areas. There is, however, no significant variation in rice prices across divisions, indicating a well integrated rice market. Rice farming and thus the welfare effect of a higher rice price vary across regions of Bangladesh primarily due to the quality of land, climate, average land ownership, proximity to metropolitan areas, technology orientation, and input availability. Geographical factors (e.g., rainfall and soil quality) influencing rice farming appear to be similar within each division. Therefore, we conduct our analysis at the divisional level. For each division, the proportions of households producing and selling rice together with a household's cultivable land holding, household income, household income from rice farming, household expenditure, and household expenditure on rice consumption are presented in Table 3.1, below.[7]

Table 3.1: Means (SD in parenthesis) of analysis sample (weighted), 2010

	Barisal	Chitt.	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	Bangladesh
Net rice seller	0.09	0.09	0.09	0.16	0.19	0.23	0.12	0.13
Self-sufficient in rice	0.12	0.10	0.10	0.15	0.14	0.15	0.11	0.12
Net rice buyer	0.79	0.80	0.81	0.68	0.67	0.62	0.77	0.75
Rice farmers	0.31	0.30	0.27	0.44	0.46	0.52	0.36	0.36
Non-rice farmers	0.69	0.70	0.73	0.56	0.54	0.48	0.64	0.64
Current household	10,632	17,668	14,997	12,100	10,477	9,178	14,013	13,476
income	(13,150)	(30,329)	(21,077)	(48,109)	(14,156)	(10,710)	(21,328)	(26,092)
Current household	760	785	806	1,210	1,641	1,926	1,409	1,126
income from rice	(1,783)	(2,063)	(2,292)	(2,339)	(4,019)	(3,642)	(3,302)	(2,803)
Household	9,684	14,302	11,534	9,251	9,167	8,265	11,971	10,926
consumption exp.	(8,002)	(12,950)	(9,585)	(7,008)	(6,911)	(6,303)	(9,323)	(9,451)
Household	1,862	1,849	1,827	1,798	1,742	1,894	2,418	1,856
expenditure on rice	(891)	(1,006)	(949)	(862)	(927)	(935)	(1,430)	(980)
N	973	2,194	3,523	1,790	1,555	1,280	856	12,171

Note: 1. Net seller, Net buyer, Autarky, Rice farmer and Non-rice farmer are dummy variables and thus indicate their proportions in our sample.
2. We define autarky households as those who produce 60-140% of their consumption of rice.

Household income usually suffers from measurement error which is typically severe in survey data from agrarian economies (Bhalotra and Attfield, 1998). In our data, we observe a significant number of households with negative or very low income. For example, 10% of the households in our sample report an income that is 60% lower than their consumption expenditure; for 25% of the households it is 40% lower; the income of almost 50% of the households is lower than their consumption expenditure, suggesting that the household income measure in our data is quite unreliable.[8]

[7] Input costs for a particular agricultural product are difficult to identify and vary with the methodology used. Therefore, we use gross income from rice farming.

[8] See Deaton (1997) for a discussion of measurement errors in household income.

3.3 Impact of a large rice price increase on welfare

3.3.1 Theoretical model

The effect of a price change on household welfare may be explained by the use of an indirect utility function.[9] Since the private savings rate of a low-income country like Bangladesh is usually low, we ignore savings in our model.[10] Consequently, we may write the indirect utility function of household i, whose income depends on the rice price p_{ir}, as follows

$$u_i \equiv v_i(p_i, x_i) = v_i[p_i, y_i + \pi_i(p_{ir})], \tag{3.1}$$

where for each household i, v_i is the indirect utility function, p_i is the price vector, x_i represents gross income, y_i represents non-rice income, and π_i represents income from rice farming.[11]

Since Bangladesh remains a net importer of rice, rice prices typically move with international rice prices. If we ignore regional variation and assume that all households face the same price, equation (3.1) can be written as

$$u_i = v_i[p, y_i + \pi_i(p_r)]. \tag{3.2}$$

Empirical studies widely use two monetary measures of welfare change, equivalent variation (EV) and compensating variation (CV). EV describes the change in the consumer's net wealth that would have an welfare impact which is equivalent to the impact of the price change. CV describes the amount of income compensation required to keep the consumer as well off after the price change as she was before (Mas-Colell, Whinston, and Green, 1995). We employ the EV measure that is

[9]Our discussion follows Deaton (1997) and Mghenyi et al. (2011).

[10]Savings in low-income countries are mostly precautionary due to inadequate income, dependency on agriculture, and absence of credit and insurance markets (Rosenzweig, 2001). Hence, expenditure levels of low-income households deviate only marginally from income.

[11]The validity of such a utility function rests on the assumption of perfect substitutability between household and hired labour in family farms. Assuming separability of goods and leisure in preferences is a standard practice (Deaton, 1997) and makes the model tractable for our analysis.

based on the initial price vector for estimating changes in welfare. Our conclusions, however, remain unchanged if we use the CV measure instead.[12]

With the utility function in (3.2), the EV measure of welfare loss for an individual i due to a rice price increase is given by

$$EV_i = e(p^0, u_i^1) - e(p^0, u_i^0), \tag{3.3}$$

where p^1 and p^0 represent the aggregate price vector with and without a change in the rice price; $e(p^k, u_i^j)$ denotes the minimum expenditure required to achieve a utility u_i^j at price p^k, while $u_i^0 = v_i[p^0, y_i + \pi_i(p^0)]$ and $u_i^1 = v_i[p^1, y_i + \pi_i(p^1)]$ measure indirect utility with associated prices and incomes.

With m_i denoting the proportional change in household i's welfare, we define EV_i as a proportional measure such that $EV_i \equiv m_i e(p^0, u_i^0)$. Hence, we can write (3.3) as

$$(1 + m_i)e(p^0, u_i^0) = e(p^0, u_i^1). \tag{3.4}$$

Therefore, at price p^0, the expenditure levels in (3.4) provide identical utility, implying that

$$v_i[p^0, (1 + m_i)e(p^0, u_i^0)] = v_i[p^0, e(p^0, u_i^1)] = u_i^1. \tag{3.5}$$

Now, from the definition of u_i^1 and using the fact that $e(p^0, u_i^0) = y_i + \pi_i(p^0)$, we get

$$v_i\left\{p^0, (1 + m_i)[y_i + \pi_i(p^0)]\right\} = v_i[p^1, y_i + \pi_i(p^1)]. \tag{3.6}$$

Taking a second-order Taylor approximation of (3.6) at $(p^1, m_i) = (p^0, 0)$, using Roy's identity and Hotelling's lemma, and solving for m_i yields

$$\begin{aligned} m_i \approx\ & (s_i^s - s_i^d)\lambda - 0.5[s_i^s \xi_i^{ps} - s_i^d \xi_i^{pd}]\lambda^2 + \\ & 0.5\{(R_i - \xi_i^{yd})[(s_i^d)^2 - 2s_i^d s_i^s] + R_i(s_i^s)^2\}\lambda^2, \end{aligned} \tag{3.7}$$

[12]The derivation of the welfare change with the CV measure is discussed in Appendix 3.A.

where for each household i, s_i^s denotes the share of rice farming in total income and s_i^d denotes the proportion of expenditure on rice to total income; λ is equal to $(p^1 - p^0)/p^0$; ξ_i^{ps}, ξ_i^{pd}, ξ_i^{yd} and R_i denotes the price elasticity of rice supply, the price elasticity of rice demand, the income elasticity of rice demand, and the coefficient of relative risk aversion (CRRA), respectively.[13] The first part on the right hand side of equation (3.7) constitutes the first round effect, whereas the remaining parts denote the second round effect of a change in the rice price on household welfare. Equation (3.7) reveals that the proportionate welfare loss caused by a higher rice price does not only depend on the surplus rice farming status, but also on other behavioural parameters.

Our estimates of the welfare impact of a price change include both the first round effect (or the immediate effect on the entitlement of households) as well as the consumption and production response to price changes, the second round effect. An analysis that is based entirely on the first round effect is appropriate if the price change is small or if other parameters in (3.7) do not differ between households. Typically some parameters differ between urban and rural households, therefore limiting the analysis to the first round impact may produce an imprecise estimate of the individual welfare loss if the price change is large.

3.3.2 Methodology

In our analysis, we employ an innovative approach of calculating the welfare loss caused by a higher rice price. In contrast to previous studies such as Mghenyi et al. (2011), we use household expenditure instead of household income which is likely to suffer from measurement error, to estimate the welfare loss. Household expenditure in our data is also less variable than household income. In addition, we capture the second order welfare effect of a price increase, while previous studies typically focus only on the first order impact. To capture the second order welfare effect of the

[13]The second-order Taylor approximation is provided in Appendix 3.B.

rice price increase, we use base values for the price elasticity of supply (ζ_i^{ps}) and the price elasticity of demand (ζ_i^{pd}) of 0.30 and 0.45, respectively. In case of the income elasticity of demand (ζ_i^{yd}), we assume a value of 0.60 for rural households, and 0.40 for urban households. In addition, throughout the analysis, we use a value of 1.0 for the coefficient of relative risk aversion, CRRA (R_i).[14] Values for these parameters are taken from the World Bank (2010). Our entire analysis of welfare changes is based on a 50% rise in the rice price, as such a high price rise, while not unprecedented, is necessary to demonstrate the contribution of the second round effect on welfare loss.

3.3.3 Results

Households' proportionate welfare losses (m_i) across divisions are presented in Table 3.2. Means of the first round proportionate welfare loss in Rajshahi and Rangpur, which are characterised as rice exporting divisions, are much lower than those of other divisions. The second round welfare changes are a significant proportion of the change in the first round, varying from 9 to 17%. For most of the divisions, the second round impact offsets part of the welfare lost in the first round. However, the second round impact intensifies the proportionate welfare loss in Rajshahi and Rangpur. Therefore, any analysis based entirely on the first round impact underestimates the proportionate welfare loss for the rice exporting divisions, and overestimates that of other divisions. However, we find a lower proportionate welfare loss among households in rice exporting divisions, indicating that households associated with rice production suffer least from the rice price increase. Importantly, using household income generates a similar but proportionately higher second round impact.[15]

[14]The second round impact is lower for lower values of CRRA. However, CRRA values do not affect our conclusions qualitatively.

[15]Results are available from the author upon request.

Table 3.2: High rice price and households' proportionate welfare loss (weighted)

	1st round (Δ_1)				2nd round (Δ_2)				Δ_2/Δ_1
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	(%)
Barisal	-0.075	0.091	-0.328	0.689	0.002	0.014	-0.152	0.023	-10.89
Chittagong	-0.049	0.078	-0.273	0.927	0.006	0.011	-0.186	0.018	-16.55
Dhaka	-0.060	0.111	-0.291	2.367	0.003	0.017	-0.363	0.018	-14.51
Khulna	-0.048	0.131	-0.323	1.680	-0.002	0.019	-0.198	0.022	-10.76
Rajshahi	-0.033	0.196	-0.275	3.834	-0.003	0.027	-0.584	0.018	-9.46
Rangpur	-0.037	0.177	-0.318	1.323	-0.007	0.025	-0.245	0.021	-8.74
Sylhet	-0.061	0.132	-0.283	1.570	-0.000	0.020	-0.243	0.018	-10.71
Bangladesh	-0.051	0.133	-0.328	3.834	0.001	0.020	-0.584	0.023	-12.61

Note: 1. $\Delta_1 = (s_i^s - s_i^d)\lambda$ and $\Delta_2 = -0.5[s_i^s\zeta_i^{ps} - s_i^d\zeta_i^{pd}]\lambda^2 + 0.5\{(R_i - \zeta_i^{yd})[(s_i^d)^2 - 2s_i^d s_i^s] + R_i(s_i^s)^2\}\lambda^2$.
2. The total proportionate welfare loss is approximated by the sum of the first round (Δ_1) and the second round (Δ_2) proportionate welfare loss.

3.4 Relationship between income and welfare loss

3.4.1 Empirical model

When analysing the relationship between income and welfare loss, studies like Deaton (1989) typically follow a non-parametric technique assuming independence between income and other explanatory variables. To relax the restriction of statistical independence of household income, Mghenyi et al. (2011) use the following semi-parametric regression model, which we followed

$$m_i = F(x_i) + Z_i\beta + u_i, \tag{3.8}$$

where for each household i, m_i represents the proportionate welfare change, x_i represents adult equivalent income, Z_i is a vector of demographic and socio-economic variables that enter the model linearly, β is a vector of parameters, F is an unknown function, and the error term $u_i \sim NID(0, \sigma^2)$.

In our model, we employ explanatory variables such as the electricity connection status, mobile phone ownership, suffering from a disaster, expenditure on chemical fertilizer, expenditure on pesticides, and input expenditure on fuel and electricity.[16] Some studies also control for the highest number of years of education in the household, which may be inappropriate in our specification because the returns to education can be non-linear. Therefore, we consider dummies for educational categories for household heads and spouses.[17] Means and standard deviations of the independent variables in the model are presented in Table 3.3 below.

Table 3.3: Means (SD in parenthesis) of independent variables (weighted)

	Barisal	Chitt.	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	Bangladesh
Family size	4.57	4.97	4.39	4.27	4.15	4.28	5.50	4.50
	(1.80)	(2.05)	(1.78)	(1.63)	(1.72)	(1.67)	(2.47)	(1.87)
HH head's age	48.00	46.41	45.28	45.52	44.75	45.53	47.53	45.75
	(14.51)	(14.21)	(13.77)	(13.25)	(13.80)	(14.00)	(14.14)	(13.90)
Household cult.	0.62	0.50	0.47	0.62	0.67	0.69	0.70	0.57
land (acre)	(1.42)	(1.53)	(1.51)	(1.39)	(1.57)	(1.45)	(2.14)	(1.53)
Mobile phone	0.60	0.71	0.72	0.61	0.60	0.42	0.61	0.64
Lean season	0.16	0.15	0.22	0.19	0.16	0.21	0.13	0.19
Female headed	0.07	0.07	0.06	0.04	0.06	0.06	0.05	0.06
Household exp.	43	56	74	212	192	166	72	113
on fertilizer	(159)	(236)	(328)	(437)	(516)	(408)	(214)	(365)
Household exp.	14	14	14	31	53	34	16	24
on pesticides	(58)	(64)	(148)	(85)	(205)	(98)	(65)	(128)
Household exp.	14	14	14	31	53	34	16	24
on electricity	(58)	(64)	(148)	(85)	(205)	(98)	(65)	(128)
Household agri.	7,339	2,908	2,451	8,751	7,869	5,373	6,175	4,887
asset value	(76,656)	(22,724)	(16,259)	(32,280)	(43,351)	(33,163)	(29,746)	(33,252)
N	973	2,194	3,523	1,790	1,555	1,280	856	12,171

Note: HH own a mobile phone, lean season and female headed household are dummy variables with means indicating their proportions.

3.4.2 Methodology and semi-parametric regression

We make several methodological changes to the approach of Mghenyi et al. (2011) when studying the relationship between welfare loss and household income. First,

[16]Suffering from a disaster may be endogenous when it is self-reported. Nevertheless, specifying the disaster type in the questionnaire reduces the likelihood of a simultaneous relation between the welfare loss and reporting a disaster.

[17]Unfortunately, our data does not include information on the distance to the next motorable road, used in some earlier studies. However, Dawson and Dey (2002) find that Bangladesh has a well-integrated and therefore competitive and efficient rice market. As a result, we may expect little impact of the distance to the next road in our model. Mghenyi et al. (2011) find that the effect of the distance to the next motorable road is only significant in two out of seven disaggregated zones of rural Kenya.

since we are interested in studying the relationship between welfare loss and permanent household income, we use household expenditure as a proxy for permanent income to estimate our semi-parametric model. Our use of household expenditure is motivated by the permanent income hypothesis, which argues that for certain life events or for changes in savings or debt, expenditure is more stable over time and therefore constitutes a better measure of welfare and economic well-being of the household than household income (Friedman, 1957). Consumption in household expenditure also captures flows from the ownership of durable goods, the insurance value of government programmes, access to credit and the accumulation of assets, while income cannot. Furthermore, household expenditure, compared to household income, is less likely to suffer from measurement error at low incomes (Meyer and Sullivan, 2012).

Unfortunately, the proportionate welfare loss and household expenditure may be jointly determined and thus the latter can be endogenous in our model.[18,19] We control for the endogeneity of household expenditure by using non-farm household income as an instrument, as the latter is closely associated with the former while having no direct impact on the dependent variable – the proportionate welfare loss. For that, we follow a methodology outlined in Newey, Powell, and Vella (1999), which involves the generation of residuals through the non-parametric regression of the endogenous variable on instruments and the use of the residuals as an additional covariate in the semi-parametric model. The advantage of this methodology is that it can generate consistent estimates of the covariates, while the significance of the residuals provides a test of endogeneity.

Second, the indirect utility function, which we use throughout the analysis, is a function of commodity price and household income. More realistically, a household's utility depends on adult equivalent income rather than household income. There-

[18]For instance, a higher rice price may increase total household expenditure and increase/reduce welfare.

[19]Similar arguments are also applicable to household income in models used by Mghenyi et al. (2011).

fore, we estimate equation (3.8) replacing adult equivalent income with (log of) adult equivalent expenditure. Earlier studies like Mghenyi et al. (2011) use adult equivalent income for such analysis. However, the study provides no hint regarding the identification of the equivalence scale. In contrast, we employ a recent semi-parametric estimate of the equivalence scale for Bangladesh provided in Hasan (2012).

For our semi-parametric estimation, we employ the local linear regression technique, using the Kernel method. We choose the local linear regression because of its performance at the boundary as well as its consistency and optimal conversion rate (Yatchew, 2003). In semi-parametric models, the selection of an appropriate bandwidth is important because the results are sensitive to the choice of the bandwidth (Yatchew, 1998). Higher bandwidths lead to a large bias with small variance, while smaller bandwidths generate large variance with small bias. Both cases imply a higher residual sum of squares and thus a higher mean squared error (MSE). One way of choosing an optimal bandwidth is to minimises the MISE, the integrated version of MSE. Optimal bandwidths in our semi-parametric models are based on the cross-validation approach. The approach is asymptotically equivalent to minimising a discrete sample approximation of MISE (Hardle and Marron, 1985). We use the Epanechnikov kernel, which constitutes the optimal kernel (Cameron and Trivedi, 2005).[20]

3.4.3 Results

The welfare loss caused by a rise in the rice price depends on permanent household income. Table 3.4 shows that the mean welfare loss declines with the increase in household expenditure, which is a proxy for permanent household income. The joint distribution of the proportionate welfare loss with regard to household expenditure, presented in Figure 3.1, reveals that the proportionate welfare change is positively correlated with household expenditure. The non-parametric regression of the pro-

[20] A semi-parametric model estimation technique is described in Appendix 3.C.

portionate welfare change on household expenditure also indicates a positive association between the two.

Table 3.4: Proportionate welfare loss (%) and expenditure quintiles by division (weighted)

	Household expenditure quintiles					All
	Quintile-1	Quintile-2	Quintile-3	Quintile-4	Quintile-5	household
Barisal	-12.1	-10.8	-8.5	-6.1	-2.9	-7.3
Rural	-12.3	-10.7	-8.5	-6.1	-2.4	-7.4
Urban	-11.1	-12.1	-8.4	-6.2	-3.9	-6.5
Chittagong	-7.0	-8.4	-6.6	-5.3	-2.2	-4.4
Rural	-7.1	-8.5	-6.6	-5.2	-1.8	-4.5
Urban	-6.9	-7.8	-6.7	-5.9	-2.9	-4.1
Dhaka	-11.6	-9.0	-7.2	-5.1	-2.7	-5.7
Rural	-11.6	-8.8	-6.6	-3.6	-2.0	-5.8
Urban	-11.5	-9.8	-9.0	-7.1	-3.1	-5.6
Khulna	-11.2	-7.4	-6.0	-3.2	-0.9	-5.0
Rural	-11.3	-6.9	-5.2	-2.2	0.1	-4.5
Urban	-10.0	-10.2	-8.7	-6.9	-2.8	-6.8
Rajshahi	-9.9	-7.4	-5.7	-2.3	4.3	-3.6
Rural	-9.7	-6.7	-5.1	-1.5	6.2	-2.9
Urban	-11.0	-10.8	-8.8	-6.2	-2.3	-7.0
Rangpur	-12.7	-9.8	-5.2	1.4	5.4	-4.3
Rural	-12.9	-9.6	-4.8	2.6	8.3	-4.1
Urban	-8.0	-11.2	-8.3	-6.5	-1.3	-5.9
Sylhet	-11.4	-10.3	-9.0	-5.5	-2.5	-6.1
Rural	-11.5	-10.2	-9.2	-5.6	-2.4	-6.5
Urban	-10.5	-13.0	-7.2	-5.4	-2.6	-4.2
Bangladesh	-11.3	-8.8	-6.6	-4.1	-1.2	-5.1
Rural	-11.3	-8.5	-6.1	-3.2	0.2	-4.9
Urban	-10.6	-10.2	-8.6	-6.7	-2.9	-5.6

Note: Author's own calculation based on HIES, 2010.

Since other explanatory variables of the proportionate welfare loss can be correlated with household income, we perform a semi-parametric (SP) regression. The residuals in our SP models, used to control for the endogeneity of household expenditure, are significant for three divisions indicating that household expenditure may be endogenous in our models. The estimates of the SP regressions are presented in Table 3.5. They show that important variables such as expenditure on chemical fertilizer, agricultural asset value, rural/urban status, suffering from disaster, and cultivable land holding are significant for most divisions.[21]

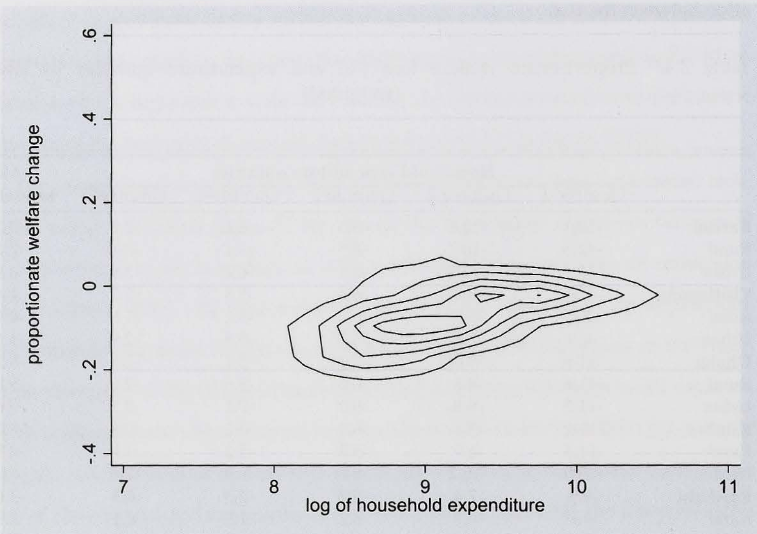

Figure 3.1: Contourlines of proportionate welfare change and household expenditure

The welfare loss may have a quadratic relationship to permanent household income. In particular, using socio-economic survey data for 1981-82, Deaton (1997) finds that the rice price increase in Thailand benefited the rural middle class. To verify the same, we present the SP regressions together with a quadratic fit in Figure 3.2. A visual inspection reveals that the quadratic fit may reasonably approximate the SP fit for most divisions. Following Hardle and Mammen (1993), we perform a specification test against a semi-parametric alternative to investigate if a quadratic fit can reasonably approximate the semi-parametric fit. The Hardle and Mammen test results, which are presented in Table 3.6, indicate that we cannot reject the null

[21] We repeat SP regressions with per capita expenditure, household expenditure and adult equivalent expenditure (equivalised using either the OECD scale or the square root of family size). All models produce similar results which are available from the author upon request. However, we only present the results for the model in which we use the semi-parametrically estimated scale to equivalent household expenditure because the scale is identified following a methodology consistent with consumer theory. Using a model that includes the rice price to control for the endogeneity of household expenditure provides similar results.

hypothesis in five out of the seven cases.[22] However, we reject the quadratic fit for the country as a whole. In contrast to our analysis with equivalent household expenditure, we cannot reject the null for any division or for the whole country when we use the per capita expenditure. There are two possible explanations for failing to reject the quadratic fit. First, richer households that are associated with agriculture benefit from selling rice at a higher price. Second, richer households that are not associated with agriculture may only lose marginally as their expenditure share on rice is usually low.

Table 3.5: Impact of independent variables on proportionate welfare change (m)

	Barishal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet	Bangladesh
Household exp.	0.019^{***}	0.011^{***}	0.006	0.011^{***}	0.014^{***}	0.007^{**}	0.035^{***}	0.011^{***}
on fertilizer	(0.007)	(0.001)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
Household agri	0.000	0.000	0.000^{**}	0.000^{**}	0.000^{**}	0.000	-0.000	0.000^{***}
asset value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lean season	-0.592	-0.161	-0.026	0.283	-1.637^{**}	0.008	1.179	-0.072
	(0.519)	(0.292)	(0.357)	(0.538)	(0.662)	(0.786)	(0.775)	(0.199)
Suffering from	1.051	0.332	1.618^{*}	0.861	2.106^{*}	3.670^{***}	-1.821^{**}	1.429^{***}
disaster	(0.718)	(0.584)	(0.854)	(0.552)	(1.245)	(0.948)	(0.866)	(0.413)
Female headed	0.932	-0.267	-0.849^{**}	2.281	5.195	0.305	-1.218	0.565
household	(0.628)	(0.404)	(0.377)	(2.192)	(4.032)	(1.047)	(0.754)	(0.601)
Urban Area	0.074	-0.435^{*}	-1.42^{***}	-0.395	-1.80^{***}	-1.861^{**}	0.953	-1.01^{***}
	(0.431)	(0.224)	(0.347)	(0.417)	(0.481)	(0.877)	(0.674)	(0.186)
Household cult.	0.593^{***}	0.610^{***}	1.060^{***}	0.537^{**}	0.735^{*}	2.660^{***}	-0.229	0.850^{***}
land (acre)	(0.181)	(0.172)	(0.358)	(0.222)	(0.387)	(0.655)	(0.305)	(0.204)
HH head's age	-0.027	-0.002	0.008	-0.043	-0.183	-0.117	0.067	-0.047
	(0.080)	(0.041)	(0.057)	(0.129)	(0.160)	(0.132)	(0.095)	(0.036)
Square of HH	0.000	0.000	0.000	0.000	0.001	0.002	-0.001	0.001^{**}
head's age	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Adjusted R^2	0.186	0.238	0.132	0.297	0.277	0.313	0.325	0.224
F	3.667	9.336	14.181	11.784	10.268	13.923	6.911	33.644
N	940	2,134	3,423	1,732	1,497	1,216	828	11,770

Note: 1. The dependent variable is the proportionate welfare change times 100.
2. Standard errors in parentheses.
3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[22] All tests are conducted at a 5 percent significance level.

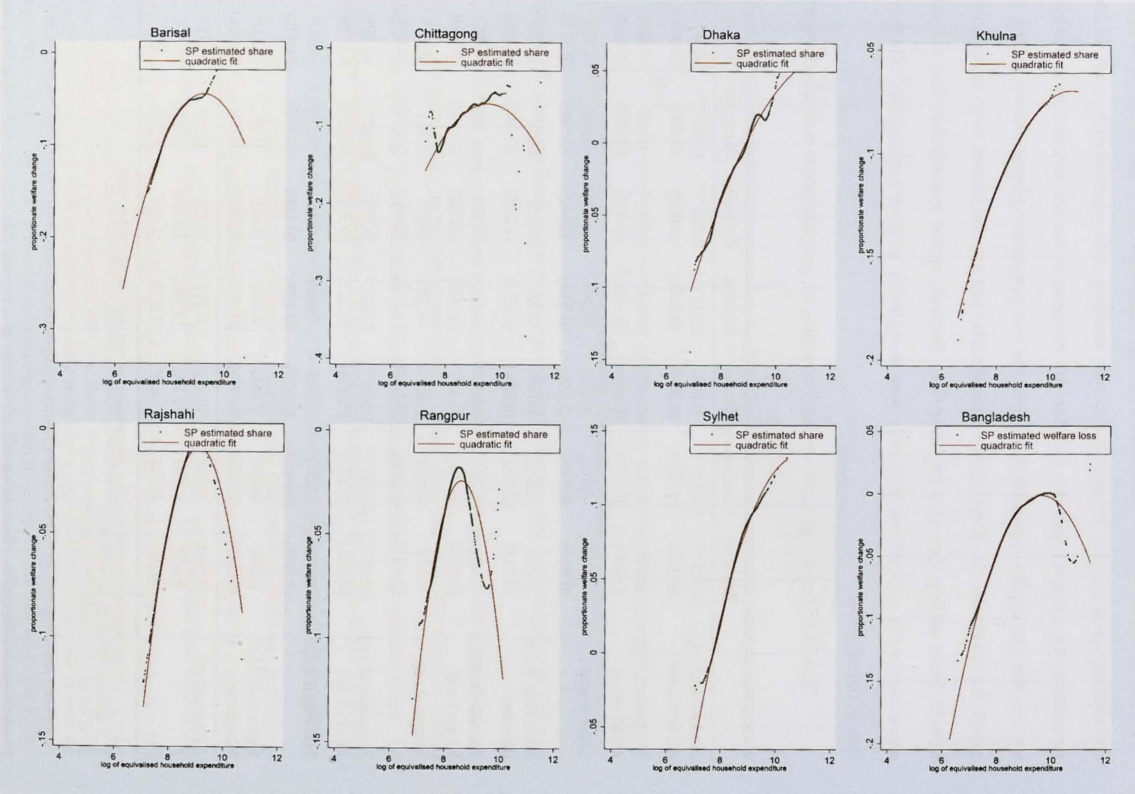

Figure 3.2: SP regression of welfare loss

Table 3.6: Hardle and Mammen test results: p-value

	With household expenditure	With per capita expenditure	With equivalent expenditure		
			SP scale	OECD scale	SRFS scale
Barisal	0.05	0.61	0.74	0.55	0.52
Chittagong	0.02	0.62	0.14	0.25	0.03
Dhaka	0.14	0.21	0.12	0.13	0.68
Khulna	0.60	0.14	0.17	0.11	0.22
Rajshahi	0.35	0.86	0.32	0.18	0.11
Rangpur	0.00	0.38	0.02	0.07	0.17
Sylhet	0.85	0.79	0.07	0.02	0.05
Bangladesh	0.00	0.00	0.00	0.05	0.00

Note: H_0 : Nonparametric fit can be approximated by a parametric adjustment of order 2, H_1 : Nonparametric fit cannot be approximated by a parametric adjustment of order 2. A low p-value rejects the quadratic fit and vice-versa. For detail, see Hardle and Mammen (1993).

A similar test using household income (equivalised with the same semi-parametric scale we used earlier) rejects the quadratic fit in three out of seven divisions as well as for the whole country. On the other hand, an analysis exclusively based on first round impacts rejects the quadratic fit in two out of seven divisions but cannot reject the quadratic fit for the whole country. These results indicate that the use of household expenditure provides conclusions that are more consistent with expectations, compared to the conclusions engendered from using household income or ignoring the second round effect.

A quadratic relation between welfare change and permanent household income indicates that the middle income household typically suffers less from the higher rice price. This highlights the need for intensified income support programmes for the poor in the face of a food price shock.

3.5 Impact of the rice price increase on poverty

3.5.1 Poverty dominance

In addition to the effect of rice price increases on welfare, policy makers are often interested in the direct and indirect effect on poverty. For that reason, we analyse the impact of a higher rice price on poverty. To study poverty, we employ the poverty measures proposed by Foster, Greer, and Thorbecke (1984) (FGT from hereon), which satisfy the property of additive decomposability. Specifically, let F: $R_{+} \rightarrow [0,1]$ represent the distribution of ordered real income such that $F(z)$ is the proportion of the population, p, with an income below or equal to z.[23] Then for each $\alpha \geq 1$, a poverty index P_{α} is given by

$$P_{\alpha}(F,z) = \frac{1}{z^{\alpha-1}} \int_{0}^{F(z)} \left[z - F^{-1}(p)\right]^{\alpha-1} dp, \tag{3.9}$$

where the measure P_1 is the poverty HCR, P_2 is the per capita income gap (a normalised measure of the poverty gap), and P_3 is the weighted sum of income shortfalls of the poor.

Uncertainty in comparing the extent of poverty arises from the disagreement about poverty lines, z, or disagreement about the poverty measures, P_{α} (Fields, 2002). Therefore, some broader criteria are useful for ordering distributions. We follow a poverty ordering outlined in Foster and Shorrocks (1988a,b) in which the poverty ordering P_{α} is such that for two distributions F and G with the same population size n

$$\begin{aligned} &FP_{\alpha}G \text{ if and only if } P_{\alpha}(F;z) \leq P_{\alpha}(G;z) \text{ for all } z \in R_{++} \\ &\text{and } P_{\alpha}(F;z) < P_{\alpha}(G;z) \text{ for some } z \in R_{++}, \end{aligned} \tag{3.10}$$

where $FP_{\alpha}G$ indicates that the distribution F implies a lower poverty level than the distribution G with respect to the poverty index P_{α} for all possible poverty lines. In other words, distribution F 'poverty dominates' distribution G, for a given α.

Therefore, the statement 'distribution F poverty dominates distribution G of first degree' implies that $F(z) - G(z) \leq 0$ for all poverty lines z with strict inequality for at least one z. Similarly, 'distribution F poverty dominates distribution G of

[23] The inverse function $F^{-1}(p)$ thus gives the income that defines the proportion of people p as poor.

second degree' implies that $\int_0^z [F(p) - G(p)]dp \leq 0$ for all poverty lines z with strict inequality for at least one z.[24] First degree poverty dominance of a distribution F on a distribution G implies that distribution F unambiguously has less poverty HCR than distribution G. Similarly, second degree poverty dominance of a distribution F on a distribution G implies that distribution F unambiguously exhibits a lower per-capita income gap than distribution G.[25] Furthermore, poverty orderings of lower order imply poverty dominance of higher order, i.e., poverty orderings are nested. Finding no dominance means that the effect of the price change on poverty is conditional on the poverty lines used.

3.5.2 Methodology

In our calculation of poverty, we replace household income with household expenditure, which is a much robust measure of household welfare. Next, incorporating the proportionate welfare loss in household expenditure, we generate a new distribution, which may represent the income distribution with the higher rice price. For convenience, we name the distribution without change in rice price as F and the distribution with the rice price change as G. We then compare distributions F and G to confirm if one distribution poverty dominates the other. Starting with the first order, we repeat our analysis for the second order if we do not find first order poverty dominance. As before, we conduct our analysis at the divisional level as well as for the whole country. Additionally, we investigate the impact of the higher rice price on the poverty headcount ratio (HCR) using official poverty lines in Bangladesh.

3.5.3 Results

Our analysis provides no evidence of first order poverty dominance for the whole country, when we consider poverty lines of up to Tk5,000.[26] However, the distribu-

[24]Some additional properties of poverty dominance are discussed in Appendix 3.D.

[25]For our purpose it is enough to confine our analysis with the first and second order poverty dominance.

[26]This corresponds to about 2.5 - 4 times the divisional poverty lines.

tion without the change in the rice price, *F*, dominates the distribution with increased rice price, *G*, for poverty lines of up to Tk3,566. As expected, critical values are lower for the rice exporting divisions compared to other divisions. This is because more than the proportionate number of surplus rice farmers in rice exporting divisions benefit from a higher rice price. With the difference between the two cumulative distributions in the vertical axis, Figure 3.3 shows no absolute first order poverty dominance of one distribution over another.

In the next step, we look for second order poverty dominance and find that for all the divisions and therefore for the whole country, distribution *F* poverty dominates distribution *G*. This implies that, if we consider the per capita income gap as a measure of poverty, the increase in the rice price unambiguously makes the country worse off. Second order poverty dominance is presented in Figure 3.4 where the vertical axis denotes the difference between the FGT indices. It shows that distribution *F* second order poverty dominates distribution *G*, i.e., distribution *F* exhibits a lower per capita income gap than distribution *G*.

An alternative analysis that is only based on the first round impact provides lower critical values for the rice exporting divisions at which distribution *G* first order poverty dominates distribution *F* and vice-versa. Most importantly, such exclusive use of the first round impact reveals no absolute second order poverty dominance for one rice exporting division, Rangpur. These findings highlight the importance of capturing the second round impact. Furthermore, repeating the analysis with household income suggests no absolute second order poverty dominance for some divisions, including one rice importing division. The poor performance of household income supports the use of household expenditure as a poverty measure.

Finally, we calculate the poverty HCR for distributions with and without a change in the rice price, using official poverty lines for each division in Bangladesh (Table 3.7). With a higher rice price, the poverty HCR increases in all divisions, but increases more in rice exporting divisions. This may seem paradoxical given that

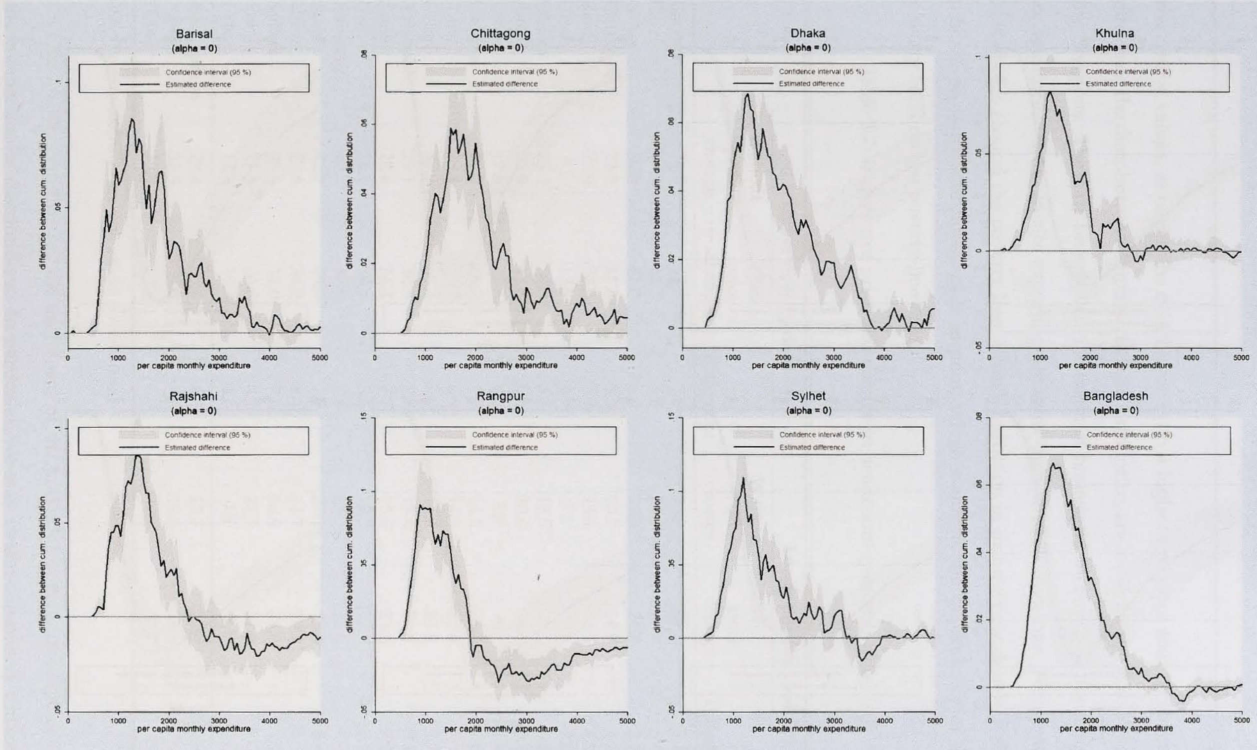

Figure 3.3: First order poverty dominance

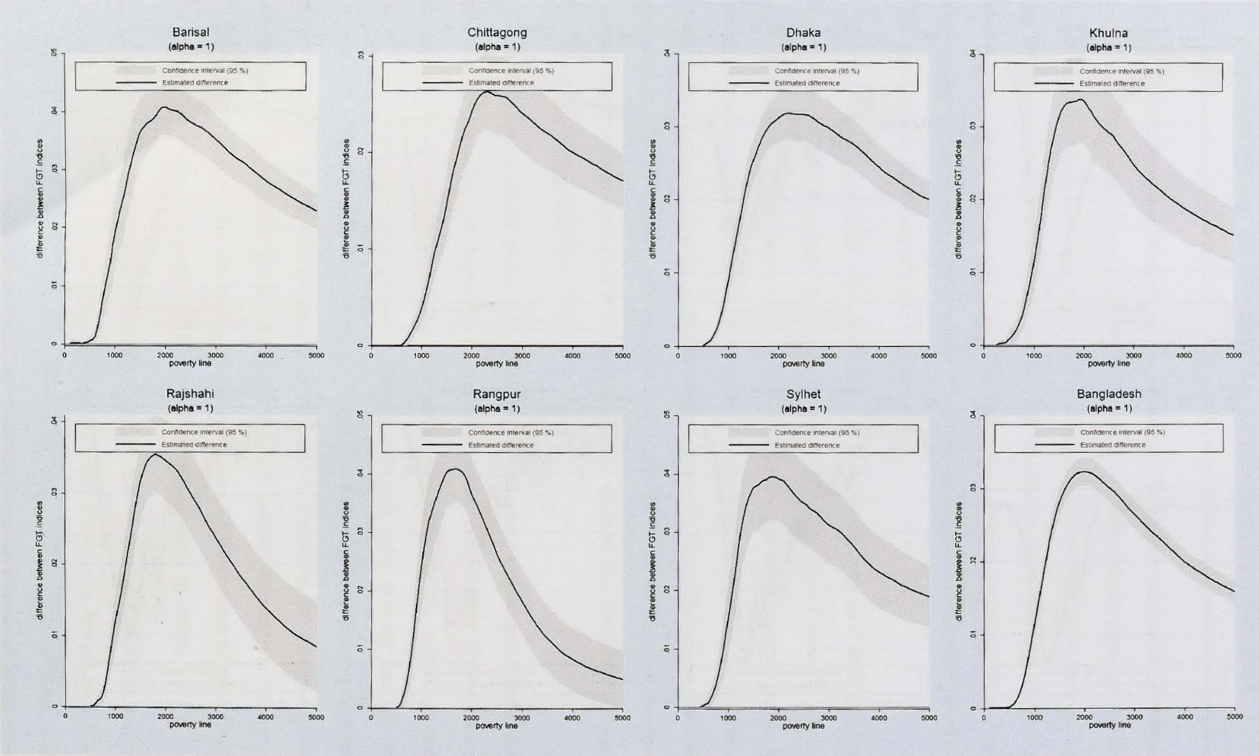

Figure 3.4: Second order poverty dominance

the critical values, at which the distribution with a higher rice price start to poverty dominate the distribution without a change in rice price, are lower for the rice exporting divisions. The data reveals that the mean of household income and household expenditure is lower in rice exporting divisions than in other divisions. With many households around the poverty line, a small reduction in income now defines a significant proportion of households as poor, which confirms the dependency of the poverty HCR on the poverty line used.

Table 3.7: Higher rice price and change in headcount (percent, weighted)

	Upper poverty line			**Lower poverty line**		
	Without price change	With price change	Difference	Without price change	With price change	Difference
Barisal	36.0	41.9	5.8	24.2	31.5	7.2
Rural	36.3	42.1	5.8	24.8	32.8	8.0
Urban	35.0	41.0	6.0	21.3	24.7	3.3
Chittagong	22.3	27.8	5.5	10.7	14.8	4.2
Rural	26.9	32.8	5.9	13.4	18.3	4.9
Urban	9.5	13.9	4.4	3.2	5.2	2.0
Dhaka	28.3	34.3	5.9	13.5	20.3	6.8
Rural	35.9	41.8	5.9	20.6	30.1	9.5
Urban	17.5	23.5	6.0	3.3	6.2	2.9
Khulna	30.0	36.7	6.7	14.5	22.3	7.8
Rural	29.4	36.2	6.9	14.5	22.4	7.9
Urban	32.3	38.3	6.0	14.2	21.9	7.7
Rajshahi	29.1	36.9	7.8	15.4	22.6	7.2
Rural	28.6	36.4	7.7	15.4	22.4	7.0
Urban	31.1	39.4	8.4	15.3	23.4	8.0
Rangpur	40.5	47.9	7.4	25.5	33.6	8.0
Rural	42.7	49.9	7.2	27.1	35.6	8.4
Urban	25.8	34.2	8.4	14.7	20.0	5.3
Sylhet	25.3	32.9	7.5	18.9	28.0	9.1
Rural	27.8	36.0	8.2	21.7	31.9	10.2
Urban	12.6	16.7	4.0	4.5	8.1	3.5
Bangladesh	29.4	35.8	6.5	15.7	22.6	6.8
Rural	32.9	39.5	6.6	19.0	26.9	7.9
Urban	19.9	25.9	6.0	6.8	10.7	3.9

Note: Poverty estimates are with official poverty lines.

Our analysis emphasises the usefulness of the notion of poverty dominance for the comparison of distributions. In particular, we may obtain completely different conclusions regarding the incidence of poverty when using different poverty lines. Therefore, using poverty lines in assessing the successes or failures of the public intervention programmes may provide wrong indications to policy makers. In addition, poverty related policies that rely on household expenditure may provide better outcomes than those that rely on household income.

3.6 Conclusion

This Chapter studies the effect of a sharp rice price increase on welfare and poverty in Bangladesh. Our analysis assesses the importance of using household expenditure as well as capturing behavioural responses to price change when estimating welfare loss. We also examine the relationship between permanent household income and welfare loss due to a higher rice price. Finally, we investigate the impact of a higher rice price on poverty.

Our study improves the estimate of welfare losses resulting from a higher rice price as we use household expenditure instead of household income which usually suffers from measurement error. We find that including the behavioural responses to price change also significantly improves the estimates of proportionate welfare loss. As a result, differences in welfare loss across regions are determined by the surplus rice farming status as well as other behavioural parameters. We investigate the relationship between welfare loss and permanent household income that is proxied by household expenditure. In our analysis we use a semi-parametric framework with control for endogeneity and employ equivalent household expenditure by using a semi-parametrically estimated equivalence scale. In our analysis, the relationship between welfare change and household income appears quadratic. We further analyse the impact of a higher rice price on poverty. For that, we again use household expenditure, a better measure of household welfare than household income. We find that changes in the head-count ratio due to a higher rice price are not invariant to the choice of poverty lines. However, when we consider the per capita income gap measure of poverty, we find that the distribution without a change in rice price generates less poverty than the distribution with a higher rice price. In both cases, our conclusions apply to all divisions or for the whole country.

We propose an improved way of estimating the proportionate welfare loss. In our method, we use household expenditure instead of household income and capture the behavioural responses to price change. In addition, we employ a better methodological framework for examining the relationship between welfare loss and permanent household income. Such models recommend a progressive income support for the poor when food prices rise. Our analysis also suggests that the success or failure of public intervention programmes may be judged better by the ranking of distributions with respect to poverty rather than by poverty estimates based on a specific poverty line. It appears that the use of household expenditure is more appropriate for poverty policy, compared to household income.

Appendix 3.A Welfare change with CV measure

We start with the same utility function in (3.2). By definition, the CV measure of a welfare loss for an individual i caused by a rice price increase from p_r^0 to p_r^1 is given by

$$CV_i = e(p^1, u_i^1) - e(p^1, u_i^0), \tag{3.11}$$

where p^1 and p^0 represents the aggregate price vector with and without the change in rice price; $e(p^k, u_i^j)$ gives the minimum expenditure required to achieve the utility u_i^j at price p^k, while $u_i^0 = v_i[p^0, y_i + \pi_i(p^0)]$ and $u_i^1 = v_i[p^1, y_i + \pi_i(p^1)]$ is the indirect utility from associated prices and income.

With m denoting the proportional change in household welfare, we define CV_i as a proportional compensating variation measure such that $CV_i = me(p^1, u_i^1)$. Hence, (3.11) can be written as

$$(1-m)e(p^1, u_i^1) = e(p^1, u_i^0). \tag{3.12}$$

Therefore, at same price p^1, utility from the expenditures in (3.12) should be identical, given by

$$v_i[p^1, (1-m_i)e(p^1, u_i^1)] = v_i[p^1, e(p^1, u_i^0)], \tag{3.13}$$

$$\Rightarrow v_i[p^1, (1-m_i)e(p^1, u_i^1)] = u_i^0. \tag{3.14}$$

Now from the definition of u_i^0 and using the fact that $e(p^1, u_i^1) = y_i + \pi_i(p^1)$ we get,

$$v_i\left\{p^1, (1-m_i)[y_i + \pi_i(p^1)]\right\} = v_i[p^0, y_i + \pi_i(p^0)]. \tag{3.15}$$

Taking a second-order Taylor approximation of (3.15) at $(p^0, m_i) = (p^1, 0)$, using

Roy's identity, Hotelling's lemma, and solving for m_i gives

$$
\begin{aligned}
m_i \approx & (s_i^s - s_i^d)\lambda - 0.5[s_i^s \zeta_i^{ps} - s_i^d \zeta_i^{pd}]\lambda^2 + \\
& 0.5\{(R_i - \zeta_i^{yd})[(s_i^d)^2 - 2s_i^d s_i^s] + R_i (s_i^s)^2\}\lambda^2, \qquad (3.16)
\end{aligned}
$$

where, as previous ζ_i^{ps}, ζ_i^{pd}, ζ_i^{yd} and R_i denotes price elasticity of rice supply, price elasticity of rice demand, income elasticity of rice demand and coefficient of relative risk aversion, respectively.[27] The difference between EV and CV lies in λ which is now equal to $(p^1 - p^0)/p^1$.

Appendix 3.B Second-order Taylor series approximation

For simplicity, we drop subscripts in (3.6), which is now given as[28]

$$
v\{p^1, (1-m)[y + \pi(p^1)]\} = v\{p^0, y + \pi(p^0)\}. \qquad (3.17)
$$

Taking a second-order Taylor approximation at $(p^1, m) = (p^0, 0)$, denoting $y + \pi(p^0)$ as x^0 and using subscripts to denote partial derivatives with respect to the subscripted variable we get,

$$
\begin{aligned}
& v(p^0) + [v_p + v_y \pi_p](p^1 - p^0) + 0.5[v_{pp} + 2v_{yp}\pi_p + v_y \pi_{pp} + v_{yy}\pi_p^2](p^1 - p^0)^2 \\
& \cong v(p^0) + v_y x^0 m + 0.5 v_{yy}(x^0)^2 m^2. \qquad (3.18)
\end{aligned}
$$

The higher order term m^2 can reasonably be ignored in the case of the second-order approximation. After reorganising, we can write (3.18) as

$$
m \approx \left[\frac{v_p}{v_y x^0} + \frac{\pi_p}{x^0}\right](p^1 - p^0) + 0.5\left[\frac{v_{pp}}{v_y x^0} + \frac{2v_{py}\pi_p}{v_y x^0} + \frac{v_{yy}\pi_p^2}{v_y x^0} + \frac{\pi_{pp}}{x^0}\right](p^1 - p^0)^2. \qquad (3.19)
$$

[27] See Mghenyi et al. (2011) for details.

[28] This section borrows from Mghenyi et al. (2011).

With q_{ir}^{d} denoting the rice consumption by household i, Roy's identity, which shows the effect of prices on utility, is given by

$$\frac{\partial v_i}{\partial p_r} = -q_{ir}^{d}\frac{\partial v_i}{\partial x_i}, \tag{3.20}$$

Similarly, with q_{ir}^{s} denoting the production of rice by household i, Hotelling's lemma, which shows the effect of prices on profits, is given by

$$\frac{\partial \pi_i}{\partial p_r} = q_{ir}^{s}. \tag{3.21}$$

Now, using Roy's identity and Hotelling's lemma and denoting $\lambda = (p^1 - p^0)/p^0$, we can write the following

$$\left[\frac{v_p}{v_y x^0} + \frac{\pi_p}{x^0}\right](p^1 - p^0) = (s_i^s - s_i^d)\lambda. \tag{3.22}$$

Denoting a household's coefficient of relative risk aversion by $R = v_{yy}x^0/v_y$, we can show that the following relationships also hold[29]

$$\frac{v_{pp}(p^0)^2}{v_y x^0} = (s^d)^2(R - \xi^{yd}) + s^d\xi^{pd}, \tag{3.23}$$

$$\frac{v_{py}\pi_p(p^0)^2}{v_y x^0} = -s^d s^s(R - \xi^{yd}), \tag{3.24}$$

$$\frac{v_{yy}\pi_p^2(p^0)^2}{v_y x^0} = R(s^s)^2, \tag{3.25}$$

$$\frac{\pi_{pp}(p^0)^2}{x^0} = -s^s\xi^{ps}. \tag{3.26}$$

Substituting those in (3.19) and reorganising gives (3.7).

[29]See Myers (2006) for details.

Appendix 3.C Semi-parametric model estimation technique

Semi-parametric model estimation technique in this Chapter follows Robinson (1988). First, we predict the dependent and all the independent variables non-parametrically using household expenditure. Second, for the dependent and all the independent variables, we obtain the difference between actual and predicted values of each variable. Third, we use OLS to estimate the coefficients of the independent variables, by regressing the differenced dependent variable on the differenced independent variables, which enter the model parametrically. We use the estimated coefficients to estimate the impact of these variables on the dependent variable. Now we subtract these estimated values (impact) from the dependent variable, so that we are only left with the impact of household expenditure on the dependent variable. Finally, we again run a non-parametric regression of the impact free dependent variable on household expenditure.[30]

For notational simplicity, we ignore subscripts i representing individuals. Now, with x representing equivalised household expenditure, our semi-parametric model is

$$m = F[log(x)] + Z\beta + v. \tag{3.27}$$

If $log(x)$ is uncorrelated with the error term, the conditional expectation of (3.27) is give by

$$E[m|log(x)] = F[log(x)] + E[Z|log(x)]\beta. \tag{3.28}$$

Estimates of the conditional moments can be obtained using the local linear regression technique. Subtracting (3.28) from (3.27) gives

$$m - E[m|log(x)] = (Z - E[Z|log(x)])\beta + v. \tag{3.29}$$

[30] This section borrows from Breunig and McKibbin (2012).

The vector β can be estimated by OLS using (3.29). We can use these estimates along with the estimated conditional moments in (3.28) to obtain an estimate of $F[log(x)]$,

$$F[\widehat{log(x)}] = E[m|\widehat{log(x)}] - E[Z|\widehat{log(x)}]\hat{\beta}. \tag{3.30}$$

In such models, household expenditure may suffer from endogeneity. To deal with this issue, we predict the residuals from a non-parametric estimation of household expenditure on household non-farm income. We then use the residuals as an additional covariate and estimate (3.29) by OLS. This procedure generates consistent estimates of the covariates, while the significance of the residuals may also indicate the presence of endogeneity.

Appendix 3.D Poverty dominance

The curve given by the plot of head-count ratios at all poverty lines (i.e., from lowest to highest income level) is known as the poverty incidence curve.[31] Each point on the curve gives the fraction of the population with an income below the amount given in the horizontal line (Figure 3.5(a)). The area under the poverty incidence curve gives the poverty deficit curve. Each point on the curve gives the sum of the poverty gap at each income level with zero gap for the non-poor (Figure 3.5(b)).

If the poverty incidence curve for one distribution F lies nowhere above another distribution G, then distribution F first-order poverty dominates distribution G.[32] As we discussed earlier, the confusion of identifying the poverty line makes the poverty dominance idea more suitable for comparing poverty. However, if we have some idea about the maximum possible poverty line – z^{max}, the same analysis can be done up to z^{max}. If we cannot find first-order poverty dominance of a particular distribution

[31]This section borrows from Ravallion (1992).

[32]Following Chen and Duclos (2011), this implies that distribution F generates more social welfare or less poverty than distribution G.

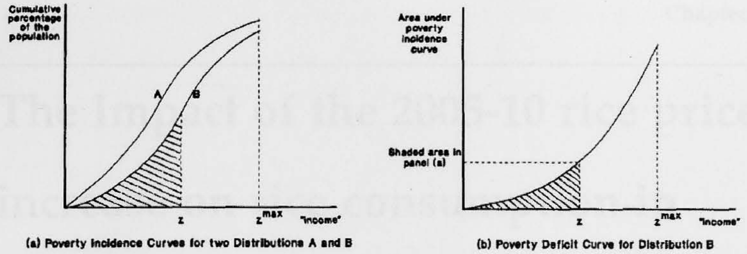

Figure 3.5: Poverty dominance
(Source: Ravallion, 1992)

over the other, we cannot order distributions by the head-count ratio.

If the poverty deficit curve of a distribution F, given by the area under the poverty incidence curve, is nowhere above of another distribution G at all points up to the maximum poverty line, then distribution F second-order poverty dominates distribution G. Second-order poverty domination order distributions in terms of the per capita income gap measure of poverty.

Chapter 4

The Impact of the 2005-10 rice price increase on rice consumption in Bangladesh[1]

Abstract

This Chapter studies the impact of rice price changes between 2005 and 2010 on rice consumption in Bangladesh, using data from the Household Income and Expenditure Survey (HIES). We compare net rice buyers and sellers to self-sufficient households and employ a difference-in-differences (DiD) estimator to determine the effect of rice price changes on household consumption. Our findings indicate that the surge in world rice prices during the late 2000s reduced the value of non-rice food consumption of net rice buyers but did not affect their value of rice or non-food consumption. At the same time, we find no significant effect of rice price changes on the rice consumption of rice sellers, but observe a positive effect on their value of non-rice food and non-food consumption.

JEL-Classification: D12, I32, O13, O53, Q12

Keywords: Rice price increase; Difference-in-difference estimation; Propensity score matching; Bangladesh.

[1]Joint work with Mathias Sinning. We thank Robert Breunig, Sanghyeok Lee, Xin Meng, Sen Xue and participants of the Crawford PhD seminar and the 83rd Annual Meetings of Southern Economic Association for helpful comments.

4.1 Introduction

Food price shocks usually hurt low-income countries around the world. At the national level, they put pressure on government budgets, deteriorate macroeconomic stability and lower the prospect of economic growth of food importing economies. At the household level, higher food prices directly affect consumption, welfare, and poverty of low-income households (Ivanic and Martin, 2008; Headey and Fan, 2008; Hasan, 2013). A low food intake induced by a high food price – even if temporary – may affect labour productivity, health outcomes, and the cognitive development of children in the long-term (World Bank, 2012).

The surge in world food prices in 2007-08 and the devaluation of the domestic currency in 2010 may have direct effects on household consumption, welfare and poverty in Bangladesh, as domestic food prices – especially rice prices – increase substantially. Strong rice price increases may have a considerable impact on food intake of a large number of households for two reasons. First, the expenditure share of rice in Bangladesh is very high, revealing a strong preference for rice consumption.[2] Second, a large proportion of households have very low incomes (Bangladesh Government, 2012b).

Some past literature investigates the impact of higher food prices in 2007-08 on the quantity and quality of food consumption (e.g. Brinkman, de Pee, Sanogo, Subran, and Bloem, 2010; Alem and Söderbom, 2010). Brinkman et al. (2010), for instance, find evidence that the increased cost of food forced households in a number of countries to reduce both quantity and quality of food consumed. A study focusing on Bangladesh further finds a significantly negative impact of the food price increase on the nutrition of women and children (Compton, Wiggins, and Keats, 2010). However, no study has analysed the impact of this event on the consumption of net rice buyer households that are expected to suffer the most.

[2]This is also indicated by a low cross price elasticity of rice demand with respect to wheat, which is the second largest household food expenditure item in Bangladesh (Ahmed and Shams, 1994; Goletti, Ahmed, and Chowdhury, 1991).

Against this background, this Chapter studies the effect of a rice price increase between 2005 and 2010 on the rice consumption of net rice buyer households in Bangladesh.[3,4] We exploit the rice price increase as a natural experiment and use data from the 2005 and 2010 Household Income and Expenditure Survey (HIES), a nationally representative household survey. We further utilise an exogenous definition to characterise households as net rice buyers, self-sufficient (autarkic) households, and net rice sellers. To identify the effect of rice price increases on consumption, we employ a difference-in-difference (DiD or double difference, DD) estimator by using autarkic households as the control group and buyer households as the treatment group. We also conduct a separate analysis with seller households (treatment group) and autarkic households (control group).

Our empirical findings indicate that the price increase between 2005 and 2010 had no significant effect on the value of rice consumption for buyer households compared to autarkic households who produce only enough rice as they need for their own consumption. Interestingly, we find a significantly negative impact of higher rice prices on the value of non-rice food consumption but no effect on non-food consumption for buyer households. In contrast, we find no significant effect on the value of rice consumption, but a positive effect on the value of both other food and non-food consumption of seller households.

The Chapter contributes to the literature on the impact of higher food prices by providing empirical evidence on food demand theory. First, we offer some support for a quadratic Engel curve for rice consumption. Second, we provide some evidence on the substitution of different food categories. Our findings may provide a valuable input to the formulation of food policies for low-income countries.

[3] The rice price increase in the world market during 2007-08 was much higher than the price increase of other food items. For instance, the rice price increased almost five times more (294%) than the wheat price (61%) (World Bank, 2010). As a result, the price increase for typical non-rice food items was relatively low compared to the rice price increase. The same is true for 2010 when the rice price increase was mainly induced by a devaluation of the domestic currency.

[4] On 15 November 2007, Bangladesh also experienced the severe cyclonic storm Sidr, which had a negative impact on agricultural harvest. However, the resulting supply shock only put transitory pressure on food prices as indicated by a minimal impact on the annual food production figure.

The remainder of this Chapter is organised as follows. Section 4.2 provides a definition of buyer, autarkic, and seller households. In Section 4.3 we discuss how the impact of a higher rice price on consumption varies depending on the type of households. Section 4.4 describes the data. Section 4.5 presents our empirical strategy and identification assumptions. Results from our analysis are presented in Section 4.6. Section 4.7 concludes.

4.2 Definition of buyer, autarkic and seller households

The results of our empirical analysis rely on the definition buyer, autarkic, and seller households. Using a possible definition of agricultural households, we could define autarkic households as those who produce about as much rice as they consume. Correspondingly, households who produce less (more) than they consume could be identified as buyer (seller) households.[5] However, such a definition would be endogenous in our model, as a higher rice price may induce farmers to produce more while consuming less. In order to use an exogenous definition for buyer, autarkic, and seller households, we use the normal daily requirement of rice (397gm per capita per day) provided in Ravallion and Sen (1996).[6] In addition, we use information on the average rice yield, provided in Bangladesh Government (2011c,d), and classify households according to whether their size of agricultural landholding allows them to produce a quantity that meets the normal daily requirement.[7]

Two other issues still have to be resolved. First, our production data only includes paddies, while the consumption data are based on rice, which is not the

[5] Occupation of the household head and rural-urban status have also been used to identify agricultural households. See Aksoy, Beverinotti, Covarrubias, and Zezza (2010) for a detailed discussion of the definition of agricultural households.

[6] This threshold depends on balanced nutrition according to the age, sex, and occupational composition of the population and is based on the Food and Agriculture (FAO) standard for South Asian countries.

[7] This will consistently classify households as long as their landholding size remains constant over time. Such a definition, however, has two limitations. First, not all agricultural households are involved in farming rice. We argue that most of the agricultural households in Bangladesh produce rice, at least for their own consumption. Second, not all types of land are equally productive. Nonetheless, the size of cultivable land may roughly indicate the type of a household.

same. Second, households typically do not consume exactly the same amount of rice that they produce. To address these issues, we only define households as buyers if their landholding – based on the 2005/06 per acre rice yield – can produce a maximum quantity of paddy that is below their required consumption. Moreover, we define non-buyer households as autarkic if they can produce a maximum quantity of paddy that is less than three times its required quantity of rice consumption.[8] The remaining households are defined as sellers.

4.3 The impact of a rice price increase on rice consumption

The impact of a rice price increase on rice consumption depends on a number of factors, including household types. In particular, we expect rice consumption of buyer households to decline more compared to autarkic households who do not rely on the market to buy or sell rice. This is because, while both types of households face a similar substitution effect, we believe that buyer households suffer from a negative income effect originating from an increase in rice price, which is not the case for autarkic households.[9,10] At the same time, opposing income and substitution effects for other food and non-food items may affect its consumption in both ways. In contrast, for seller households, we expect the price increase to have a positive income effect and a negative substitution effect on rice consumption, resulting in an ambiguous total effect. Correspondingly, we expect that both income and substitution effects, engendered from the higher rice price in 2010, will positively affect the consumption of non-rice food and non-food items of seller households.

A comparison between buyer and autarkic households is depicted in Figure 4.1,

[8]To identify the income effect, what matters is income net of input costs for which we have insufficient information. We expect our definition for buyer, autarkic, and seller households to take care of the difference between rice and paddy on the one hand, and input costs on the other hand. Our conclusions, however, are not affected by reasonable modifications of our definitions.

[9]We assume that the impact of a rice price increase on production is negligible. A limited size of agricultural land, a huge dominance of rice in farming and a high cropping intensity has only left limited scope for production to respond to a higher rice price.

[10]Nonetheless, a very inelastic demand would only result in a marginal difference in the quantity or value of rice consumption between these two types of households.

where the rice demand for autarkic and buyer households is given by a compensated and an uncompensated demand curve. At an initial price P_0, both types of households consume a quantity equal to OS. Other things equal, a change in the price to P_1 has no effect on the income of autarkic households. However, the substitution of rice for other goods is now relatively costly for autarkic households, resulting in a decline in rice consumption by the quantity SE. The same price change reduces rice consumption of buyer households by an additional quantity (IE). The reason is that while both households types experience an identical substitution effect, buyer households suffer from an additional income effect. As a result, the quantity of rice consumption of buyer households is reduced by IS, compared to the reduction SE for autarkic households.

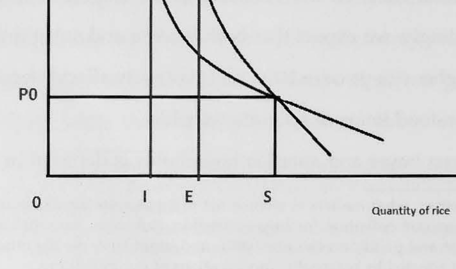

Figure 4.1: Effect of a rice price increase on autarkic and buyer households

4.4 Data

The study uses data from the 2005 and 2010 rounds of the Bangladesh Household Income and Expenditure Survey (HIES). The HIES is a repeated cross-section survey and is conducted every 3-5 years to generate nationally representative socio-economic information at the individual and household level. The selection of households in the survey is based on a two-stage stratified random sampling approach under the framework of an integrated multi-purpose sample design. The total number of households in the 2005 and 2010 rounds of the survey is 10,080 and 12,240, respectively (Bangladesh Government, 2007, 2012b).

As there are different varieties and qualities of rice in the country, in Table 4.1 we present the price of rice disaggregated into three major qualities for three different types of households we defined earlier. Our household level data, like aggregate price data for Bangladesh, shows a substantial rice price increase between the two surveys. However, there is no significant variation in the rice price across regions. This is consistent with some earlier studies, which identify the rice market in Bangladesh as well integrated (e.g. Dawson and Dey, 2002). Interestingly, buyer households encounter a slightly higher price compared to other types of households. On the other hand, as expected, autarkic and seller households report a similar price.

Table 4.1: Rice price (BDT/kg) by household category (weighted), 2005 & 2010

	2005			2010		
	Buyer	Autarkic	Seller	Buyer	Autarkic	Seller
High quality rice	31.32	31.70	29.81	65.79	63.39	58.98
price	(8.56)	(7.05)	(7.79)	(21.32)	(21.36)	(18.31)
Medium quality rice	17.74	17.38	17.77	35.66	34.34	34.17
price	(2.25)	(2.31)	(4.08)	(4.27)	(3.71)	(4.12)
Low quality rice	16.92	16.73	16.82	30.68	30.59	30.28
price	(2.87)	(1.26)	(1.31)	(2.64)	(2.60)	(2.71)
Average rice price	17.25	17.03	17.25	33.11	32.64	32.48
	(1.87)	(1.77)	(1.88)	(4.64)	(4.05)	(4.55)
Observations	6,386	1,292	856	9,423	1,665	1,073

Note: Standard deviations in parenthesis.

Table 4.2 shows the quantities of rice consumption for different types of households, again disaggregated into three major qualities. Based on our definition, mean quantity of rice consumed by autarkic households is higher compared to buyer households but similar to that of seller households. In addition, for all categories of households, low quality constitutes most of the consumption in rice. The availability of different qualities of rice, however, allows households to switch to a cheaper variety in response to an increase in the rice price.[11] As we see in Table 4.2, all categories of households reduce their consumption of rice over time with buyer households reducing at a slightly lower rate (12%) compared to autarkic households (15%). Interestingly, compared to buyer households, a higher proportion of the reduction in rice consumption for autarkic households comes from the low quality rice. As a result, low quality rice consumption declines from 61 to 56% for autarkic households and from 64 to 62% for buyer households.

Table 4.2: Consumption of rice (kg) by household category (weighted), 2005 & 2010

	2005			2010		
	Buyer	Autarkic	Seller	Buyer	Autarkic	Seller
High quality rice	0.60	0.58	1.62	0.90	1.36	2.01
consumption	(4.76)	(4.68)	(10.16)	(5.96)	(9.04)	(13.25)
Medium quality rice	21.71	28.54	31.16	19.91	26.50	24.88
consumption	(34.54)	(42.24)	(46.83)	(29.80)	(36.49)	(38.42)
Low quality rice	40.35	44.75	41.88	34.53	35.25	34.89
consumption	(37.69)	(45.24)	(49.61)	(35.22)	(39.32)	(40.83)
Total rice	62.66	73.86	74.67	55.35	63.11	61.78
consumption	(31.06)	(37.79)	(47.13)	(28.40)	(33.01)	(39.48)
Observations	6,386	1,292	856	9,423	1,665	1,073

Note: Standard deviations in parenthesis.

The presence of three different qualities of rice complicates an analysis that is based on quantity. Therefore, we prefer to focus on the value of consumed rice as this provides a relatively straightforward answer to the question we are interested in. Table 4.3 below shows an increased value of rice consumption over time, reflecting

[11] For a detailed analysis on the quality issue, see Deaton (1997). To address the issue of unit value vs. price, we use prices for three different qualities of rice that are available in the data.

mainly the rise in its price.

Table 4.3: Summary statistics of household rice consumption value (BDT) by household type (weighted), 2005 & 2010

	2005			2010		
	Buyer	Autarkic	Seller	Buyer	Autarkic	Seller
Mean	1,073	1,246	1,274	1,809	2,038	1,984
SD	531	634	778	917	1,066	1,279
Min	44	64	39	44	147	65
Max	5,534	5,969	6,588	9,150	9,170	13,908
Percentiles of consumption value						
10	499	553	518	837	926	776
25	712	824	743	1,172	1,307	1,159
50	985	1,128	1,098	1,647	1,834	1,704
75	1,342	1,549	1,588	2,288	2,582	2,451
90	1,725	1,982	2,222	2,967	3,333	3,521
Observations	6,386	1,292	856	9,423	1,665	1,073

Note: Standard deviations in parenthesis.

Summary statistics of a set of demographic and socioeconomic variables, which we used in our analysis, are presented in Table 4.4. The table shows that agricultural households have a larger family size. Looking into our data we also find farmers to report in-kind input expenditure for rice farming (e.g., storing as seed and paying to the landlord and labourers). Adjustments for family size and in-kind expenditure may explain the variation in mean consumption quantity of rice among groups, which we found earlier.

We generally find a reduction in family size (mainly children) for all categories of households over time (Table 4.4). We further observe an increase in the highest year of schooling of household members, a reduction in the size of landholding and an increase in household income and expenditure. In general, autarkic households have a higher (lower) income and consequently a higher (lower) total consumption expenditure compared to buyer (seller) households. The former group exhibits a larger family size as well as a larger holding size of land. In addition, the mean age of the household head is higher for autarkic households, who also have a higher propensity to live in a rural area. The scenario is similar for both survey years – 2005 and 2010. Given that autarkic households are mainly farmers, this pattern is consistent with what is usually observed in reality. Interestingly, autarkic households are roughly similar to seller households, except for the finances. This similarity is expected as both are agricultural households but by definition the latter has a higher per capita landholding size compared to the former.

Table 4.4: Summary statistics of independent variables by household type (weighted), 2005 & 2010

	2005			2010		
	Buyer	Autarkic	Seller	Buyer	Autarkic	Seller
Demographics						
Family size	4.77	5.13	4.82	4.51	4.65	4.19
	(1.97)	(2.22)	(2.37)	(1.84)	(1.96)	(1.94)
No. of adults in	2.52	2.88	3.02	2.52	2.81	2.75
household	(1.12)	(1.39)	(1.56)	(1.11)	(1.31)	(1.23)
No. of kids in	2.25	2.24	1.80	1.99	1.84	1.44
household	(1.46)	(1.49)	(1.44)	(1.36)	(1.36)	(1.30)
Household head's age	43.73	47.61	51.22	44.33	49.51	52.05
	(13.15)	(13.24)	(14.66)	(13.46)	(13.89)	(14.79)
Female headed hh	0.10	0.10	0.09	0.05	0.05	0.07
	(0.30)	(0.30)	(0.29)	(0.23)	(0.22)	(0.25)
Regional Status						
Urban	0.29	0.16	0.17	0.30	0.15	0.15
Education						
Highest school year	5.62	7.90	9.43	6.28	8.32	8.98
in the household	(4.45)	(4.11)	(4.31)	(4.30)	(4.15)	(4.51)
Landholding						
HH's cultivable land	0.09	1.30	4.31	0.08	1.18	3.89
in acre	(0.21)	(0.68)	(3.89)	(0.18)	(0.63)	(3.48)
Other						
Lean Season	0.18	0.15	0.15	0.19	0.18	0.14
Finances						
Total household	6,256	9,252	15,339	10,394	16,206	20,548
income	(11,903)	(17,912)	(40,563)	(14,572)	(47,888)	(24,052)
Household	5,442	6,913	9,085	10,183	12,342	15,200
consumption expenditure	(5,320)	(5,734)	(8,113)	(8,619)	(8,915)	(14,531)
Observations	6,386	1,292	856	9,423	1,665	1,073

Note: Standard deviations in parenthesis.

4.5 Empirical strategy and identification

The rice price increase between 2005 and 2010 was an exogenous event for a small rice importing country like Bangladesh, as the domestic price followed the movement of both the global price as well as the domestic exchange rate. Figure 4.2 below shows that the wholesale price of coarse (quality) rice in Bangladesh starts rising from early-2007 until the end of 2008 and then falls until end-2009 and then starts to rise again. Two vertical dotted lines in the figure show the mean rice price in July 2005 and July 2010, around which the survey data were collected, which was BDT15.57 and BDT27.85, respectively. However, the rice price in the international market was relatively stable after 2008 (Fig 4.3).[12] The depreciation in the domestic currency, presented in Figure 4.4, explains the rise in the rice price in Bangladesh during 2010 and afterwards. Such a price change can be considered as exogenous and allows us to investigate the consumption pattern of households before and after the price change as we do in any natural experiment.

We use a difference-in-difference model to identify the impact of a higher rice price in 2010 on the consumption of net rice buyer households, compared to their consumption in 2005. Our empirical model is given by

$$Y_{it} = \alpha + \beta Y_{2010} + \gamma Buyer_i + \delta Buyer_i * Y_{2010} + \psi X_i + u_i, \tag{4.1}$$

where Y_{it} denotes the quantity/value of consumed rice of household i at period t = {2005, 2010}, Y_{2010} is a dummy for the price change (realised in 2010), $Buyer_i$ is a dummy indicating if the household is a net rice buyer, X_i is a vector of other explanatory variables and u_i is the error term. The parameter δ – the DiD estimator – measures the effect of a higher rice price on buyer households.

[12]The export of rice from India was restricted for few months during 2007-08. Therefore, we present the export price of rice from Thailand. Our reported price is for parboiled rice, the main type that is imported to Bangladesh.

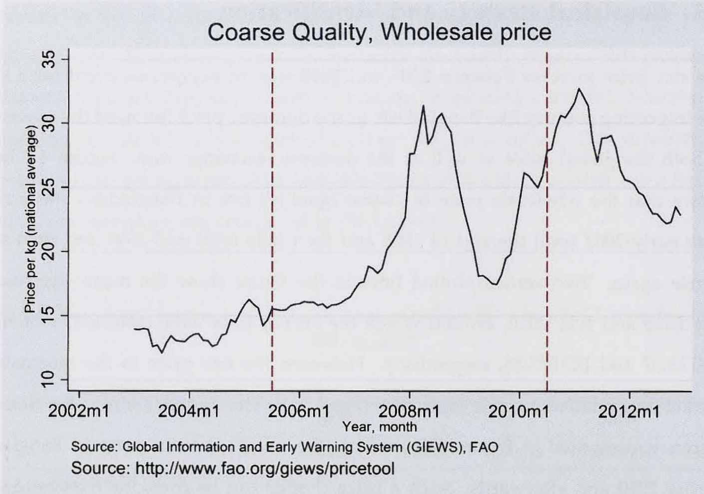

Figure 4.2: Movement in the wholesale price of low-quality rice

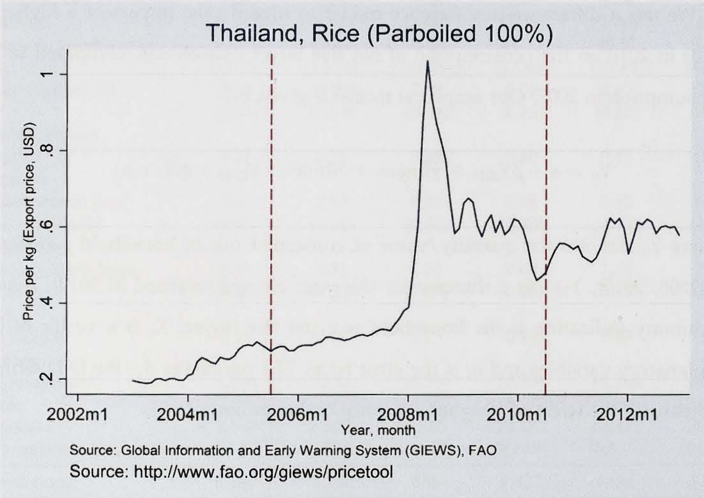

Figure 4.3: Movement in the world price of low-quality rice

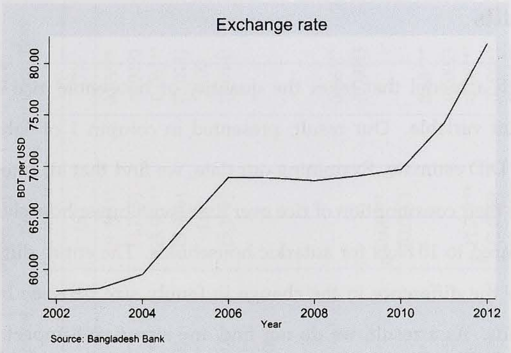

Figure 4.4: Movement in the exchange rate: annual averages

In our model, we control for family size, household income, parental education, agricultural asset value and season. In addition, to control for some determinants of rice production like soil quality and irrigation facility that are difficult to capture, we use dummies for divisions and urban/rural status as well as agricultural input expenditure. We also use a similar set of variables in combination with a propensity score matched DiD estimate to control for the selection bias between autarkic and buyer households.

To identify the DiD estimate in our model, we make a few assumptions. First, the error term u_i is independent of the group identifier (buyer/seller). Second, the distribution of u_i remains unchanged over time. Together, these assumptions imply that in the absence of the treatment (price change), the unobserved differences between the control and the treatment groups would have remained unchanged over time. We ensure the first assumption through providing an exogenous definition for the groups. The second assumption, which implies the underlying trend in the dependent variable to be the same for both the treatment and the control group, is never testable but appears reasonable in our settings. As a result, we expect that our DiD estimator identifies the average treatment effect (ATE), i.e., average effect of the price change on the consumption of net rice buyer households.

4.6 Results

We start with a model that takes the quantity of household rice consumption as the dependent variable. Our result, presented in column 1 of Table 4.5 shows an insignificant DiD estimate. Examining our data, we find that all categories of households reduce their consumption of rice over time, with buyer households reducing by 7.3kgs compared to 10.8kgs for autarkic households. The entire difference is almost explained by the difference in the change in family size between buyer and autarkic households. As a result, we do not find any significant impact on the quantity of rice consumption for buyer households. Following the same argument, our use of per capita rice consumption quantity also provides a similar result, presented in column 2 of the same table.

Next, we use the consumption value, which may better capture the difference in the quality of rice consumed by buyer and autarkic households. Our result with the value of household rice consumption as the dependent variable, presented in column 3 of Table 4.5, shows a clear reduction in consumption that is significant at the 1% level. In our estimate, the value of consumed rice is roughly 5% lower for buyer households, compared to that of autarkic households in 2010, which is due to the higher rice price. As demographic characteristics – particularly household size – are important determinants of food expenditure, we repeat the same analysis, but now with per capita value of rice consumption. Again, we find a negative DiD estimate, which is significant at the 5% level, presented in column 4. Our DiD estimate is diagrammatically presented in Figure 4.5 below.

Our previous analysis is valid only when members of both groups are selected randomly. This may not always be the case.[13] For example, Naik and Moore (1996) find habit important to determine food consumption. Agricultural households, because of their job nature, may have a different consumption pattern compared to non-agricultural households. Propensity score matching (PSM) may help us to get

[13]Particularly, if someone views our setting as a quasi experiment rather than a natural experiment.

Table 4.5: Effect of the 2005-10 rice price increase on rice consumption of buyers

	Household quantity of rice consumption	Per capita quantity of rice consumption	Value of household rice consumption	Value of per capita rice consumption	PSM value of household rice consumption	Inflation adjusted value of per capita rice consumption	Log value of household rice consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year2010	-4.31***	-0.78***	926.67***	193.56***	927.12***	89.20***	0.55***
	(0.705)	(0.155)	(20.551)	(4.458)	(20.575)	(4.749)	(0.013)
Buyer	-6.09***	-1.17***	-57.08***	-18.46***	-59.62***	-25.98***	-0.06***
	(0.582)	(0.128)	(16.974)	(3.682)	(17.001)	(3.946)	(0.011)
Year2010*Buyer	1.25	0.19	-100.05***	-12.09**	-95.59***	-4.67	0.00
	(0.765)	(0.169)	(22.285)	(4.838)	(22.327)	(5.172)	(0.014)
Total household income	-0.00*** (0.000)		0.00 (0.000)		0.00 (0.000)		
Per capita income		0.00**		0.00***			
		(0.000)		(0.000)			
Log of HH total income							0.06*** (0.004)
Inflation adjusted PC total income						0.00*** (0.000)	
Family size	11.76***		299.97***		299.99***		0.19***
	(0.074)		(2.160)		(2.170)		(0.002)
Urban	-7.24***	-1.56***	-87.42***	-18.41***	-81.65***	-21.77***	-0.08***
	(0.305)	(0.067)	(8.894)	(1.932)	(9.027)	(2.068)	(0.006)
Constant	12.64***	14.42***	-386.80***	226.69***	-383.55***	331.40***	5.51***
	(0.772)	(0.143)	(22.490)	(4.110)	(22.660)	(4.417)	(0.032)
Adjusted R^2	0.623	0.130	0.624	0.387	0.625	0.145	0.631
F	1,295.44	122.98	1,301.28	516.46	1,293.14	139.36	1,339.11
N	18,766	18,766	18,766	18,766	18,585	18,766	18,766

Note: 1. Standard errors in parentheses.
2.* p <0.10, ** p <0.05, *** p <0.01.

rid of selection issues if the selection is based on the observable characteristics of households. Consequently, we use a propensity score matched DiD estimate assuming that unobservable characteristics do not affect household's net rice buying status. In that model we weight observations according to their propensity scores.[14] Again, we find results, presented in column 5 of Table 4.5, which are similar to the case when we do not address the selection issue.[15] Almost all important explanatory variables in our model are significant at the 1% level and have the correct sign. For instance, urban status affects rice consumption negatively while income and family size affects rice consumption positively.

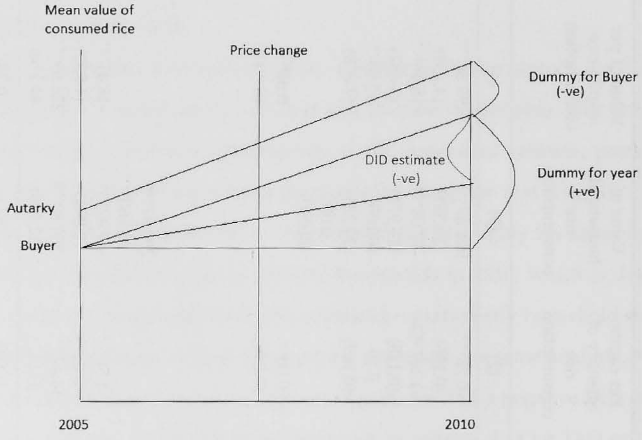

Figure 4.5: DiD estimate

[14]The purpose of such weighting is to generate a fully efficient estimator (Khandker, Koolwal, and Samad, 2010). However, our results are insensitive to the use of such weights.

[15]It is to be noted that not all variables are balanced in each block, which we define during applying the PSM technique. However, this is only the case for a small number of variables and blocks. Therefore, we interpret our result as usual.

Because our consumption data is nominal, the difference in initial consumption may be exaggerated due to a higher price level. When we use inflation adjusted price in our analysis, which is our preferred model, we find a negative but insignificant impact on the value of rice consumption for buyer households, which is due to the price increase (column 6 of Table 4.5). This is true regardless of our use of household or per capita value of the dependent variables. Arguably, a choice of the index for inflation is subjective, which can be avoided using the logarithm of the dependent variable. However, such models provide results, which only indicate percentage difference in the dependent variable between groups. Our DiD estimate in column 7 of Table 4.5 reports results using the log of household's rice consumption value as the dependent variable. The results show that both types of households change their real value of rice consumption in a similar proportion.

It is interesting to investigate how households compensate their dietary requirement when they face a rice price shock. To do so, we conduct the same analysis but now for other food, excluding rice. Our results in column 1 of Table 4.6 indicate a significant negative impact on non-rice food expenditure for buyer households. The use of the per capita value, presented in column 2 of Table 4.6, also indicates a significant and negative impact on non-rice food expenditure of buyer households. Our preferred model, in which we use inflation adjusted prices, again shows a significantly negative impact of the price increase on the value of (household or per capita) non-food consumption for buyer households (column 3 of Table 4.6). However, using the logarithm of non-rice food consumption value as the dependent variable indicates a similar proportional change in its consumption for buyer and autarkic households (column 4 of the same table). As found previously, all important explanatory variables used in our analysis are significant at the 1% level. In line with our expectation, urban status has a positive impact on non-rice food consumption.[16]

[16]Our results are insensitive to the choice of independent variables except for family size. Furthermore, our conclusions remain unaffected even if we exclude buyer households who also produce some rice.

Table 4.6: Effect of the 2005-10 rice price increase on non-rice food and non-food consumption of buyers

	Value of household non-rice food consumption	Value of per capita non-rice food consumption	Inflation adjusted value of per capita non-rice food consumption	Log value of household non-rice food consumption	Value of household non-food consumption	Value of per capita non-food consumption	Inflation adjusted value of per capita non-food consumption	Log value of household non-food consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year2010	2250.16***	499.64***	306.31***	0.58***	1968.62***	450.64***	195.39***	0.42***
	(73.631)	(17.067)	(17.848)	(0.017)	(167.143)	(38.363)	(41.638)	(0.020)
Buyer	-212.92***	-50.17***	-71.94***	-0.11***	-471.22***	-84.15***	-134.23***	-0.18***
	(60.816)	(14.094)	(14.827)	(0.014)	(138.052)	(31.680)	(34.592)	(0.017)
Year2010*Buyer	-354.78***	-65.68***	-41.26**	0.02	-251.18	-70.83*	-11.08	0.04*
	(79.846)	(18.520)	(19.435)	(0.019)	(181.250)	(41.628)	(45.342)	(0.022)
Total household income	0.02***				0.06***			
	(0.001)				(0.002)			
Per capita income		0.02***				0.07***		
		(0.001)				(0.002)		
Log of HH total income				0.28***				0.37***
				(0.005)				(0.006)
Inflation adjusted PC total income			0.02***				0.08***	
			(0.001)				(0.002)	
Family size	436.95***			0.10***	512.37***			0.10***
	(7.739)			(0.002)	(17.567)			(0.002)
Urban	738.42***	163.99***	178.38***	0.17***	1254.22***	273.52***	303.73***	0.22***
	(31.868)	(7.396)	(7.772)	(0.008)	(72.339)	(16.625)	(18.131)	(0.009)
Constant	143.27*	481.33***	667.01***	4.72***	-503.16***	381.29***	594.22***	3.92***
	(80.577)	(15.733)	(16.598)	(0.041)	(182.910)	(35.364)	(38.722)	(0.048)
Adjusted R^2	0.462	0.378	0.318	0.644	0.309	0.289	0.277	0.633
F	673.46	496.09	381.13	1,418.01	350.51	333.24	312.96	1,347.59
N	18,766	18,766	18,766	18,766	18,766	18,766	18,766	18,759

Note: 1. Standard errors in parentheses.
2.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Further, we investigate the impact on households' value of non-food consumption. Our results in column 5-6 of Table 4.6 show an insignificant negative impact on buyers regardless of our use of household or per capita value. Using inflation adjusted prices in our analysis, we again find no significant impact of the price increase on the value of other food consumption (column 7 of Table 4.6).[17] Again, all important explanatory variables used in our analysis with the value of total consumption have the correct sign and are significant at the 1% level. Like the case for non-rice food, urban status positively affects total consumption.[18] Finally, using the logarithm of non-food consumption also shows an insignificant DiD estimate (column 8).

In turn, the previous analysis reveals a significantly negative impact of a higher rice price on the value of rice consumed by buyer households. However, this difference disappears when we adjust for inflation.[19] Our model with a logarithm of the value of rice consumption indicates that both buyer and autarkic households have a similar price elasticity of rice demand. An analysis with non-rice food items indicates that a strong rice preference forces buyer households to reduce their consumption of other food items. Nonetheless, the rice price increase does not affect the non-food consumption of buyer households differently from autarkic households.[20]

We also conduct a similar analysis with seller households while again using autarkic households as the control group. Results in Table 4.7 indicate that, the price increase does not significantly change either the quantity or the value of rice consumption for seller households. This result holds true even if we control for the change in the price level. Again, all controls have the correct sign and almost all are significant at the 1% level.

[17] This is also true for our use of household or per capita value of the dependent variables.

[18] Again, our results are insensitive to the inclusion of independent variables except for family size.

[19] The reason is that the nominal value of rice consumption for autarkic households has been elevated by a higher price, as they consume a higher quantity of rice.

[20] Models with the value of household/per capita non-food consumption as the dependent variable are sensitive to the inclusion of socioeconomic variables in our model. This focuses on a greater role of households' socioeconomic characteristics in determining non-food consumption compared to food consumption.

Table 4.7: Effect of the 2005-10 rice price increase on rice consumption of sellers

	Household quantity of rice consumption	Per capita quantity of rice consumption	Value of household rice consumption	Value of per capita rice consumption	PSM value of household rice consumption	Inflation adjusted value of per capita rice consumption	Log value of household rice consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year2010	-3.23***	-0.72***	952.03***	195.91***	952.03***	90.48***	0.55***
	(0.879)	(0.190)	(24.661)	(5.258)	(24.661)	(5.680)	(0.014)
Seller	5.94***	1.47***	145.70***	29.38***	145.70***	40.61***	0.03*
	(1.049)	(0.227)	(29.412)	(6.285)	(29.412)	(6.827)	(0.017)
Year2010*Seller	-0.38	-0.14	-28.08	11.03	-28.08	1.31	-0.03
	(1.382)	(0.299)	(38.768)	(8.299)	(38.768)	(9.001)	(0.022)
Total household income	-0.00		0.00		0.00		
	(0.000)		(0.000)		(0.000)		
Per capita income		0.00		0.00**			
		(0.000)		(0.000)			
Log of HH total income							0.05***
							(0.007)
Inflation adjusted PC total income						0.00***	
						(0.000)	
Family size	13.44***		328.56***		328.56***		0.18***
	(0.165)		(4.616)		(4.616)		(0.003)
Urban	-11.08***	-2.29***	-182.85***	-35.88***	-182.85***	-40.80***	-0.13***
	(0.838)	(0.182)	(23.502)	(5.033)	(23.502)	(5.456)	(0.013)
Constant	3.81**	14.54***	-527.71***	233.16***	-527.71***	338.94***	5.60***
	(1.487)	(0.261)	(41.713)	(7.234)	(41.713)	(7.857)	(0.059)
Adjusted R^2	0.626	0.146	0.606	0.373	0.606	0.155	0.623
F	341.25	37.32	313.69	127.54	313.69	40.00	336.69
N	4,886	4,886	4,886	4,886	4,886	4,886	4,886

Note: 1. Standard errors in parentheses.
2.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Now, we focus on the value of non-rice food consumption as well as non-food consumption for seller households. The results in Table 4.8 indicate a significant increase in both, resulting from a higher rice price. As most of the consumption goods are normal, and seller households suffer from a positive income and substitution effect, consumption of both non-rice food and non-food items increase significantly. Interestingly, the proportionate increase in non-rice food and non-food consumption are similar to that of autarkic households. This is shown by insignificant DiD estimates in column 4 and 8, where we use the logarithm of the dependent variable in our model.[21]

Our analysis, which uses the value of rice consumption as the dependent variable, suggest that the Engel curve for rice is non-linear. This is because when we control for inflation, we find a similar impact on the value of rice consumption for all types of households. The insensitive consumption in the face of an income effect is feasible with a quadratic Engel curve, which indicates that households do not change their consumption considerably with income. This is consistent with some earlier studies, which find a quadratic food Engel curve for some developing countries including Bangladesh (e.g., Bhalotra and Attfield, 1998; Hasan, 2012).

In our analysis we control for the rural/urban status of a household. However, if parameters are different for rural and urban households, we obtain different results. Therefore, we repeat the analysis separately for urban and rural households and control for divisions. However, our earlier findings are unaltered in the new settings. Another particular concern about our previous analysis is that the treatment is not uniform within groups. Furthermore, the control group is also subject to the treatment, though to a lesser extent.[22] To address this issue, we again use our previous specification but now replace the dummy for buyers with a household's landholding size. We expect both landholding and its interaction to positively affect the value of non-rice food and non-food consumption, although we do not know

[21]Our results involving the sample of seller households are robust to the inclusion of independent variables except family size.

[22]Nonetheless, we believe that the treatment effect increases with farming capacity.

Table 4.8: Effect of the 2005-10 rice price increase on non-rice food and non-food consumption of sellers

	Value of household non-rice food consumption	Value of per capita non-rice food consumption	Inflation adjusted value of per capita non-rice food consumption	Log value of household non-rice food consumption	Value of household non-food consumption	Value of per capita non-food consumption	Inflation adjusted value of per capita non-food consumption	Log value of household non-food consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year2010	2398.36***	518.85***	317.54***	0.61***	2293.76***	509.38***	229.52***	0.44***
	(98.390)	(23.040)	(24.435)	(0.018)	(237.454)	(61.377)	(66.227)	(0.022)
Seller	580.74***	129.69***	195.36***	0.13***	1098.85***	237.84***	377.54***	0.17***
	(117.347)	(27.541)	(29.373)	(0.021)	(283.203)	(73.367)	(79.611)	(0.026)
Year2010*Seller	385.95**	196.65***	130.33***	-0.03	1139.69***	399.26***	246.95**	-0.03
	(154.675)	(36.365)	(38.724)	(0.028)	(373.290)	(96.875)	(104.956)	(0.034)
Total household income	0.01***				0.03***			
	(0.001)				(0.003)			
Per capita income		0.01***				0.04***		
		(0.001)				(0.003)		
Log of HH total income				0.23***				0.35***
				(0.009)				(0.011)
Inflation adjusted PC total income			0.01***				0.04***	
			(0.001)				(0.003)	
Family size	549.83***			0.10***	707.62***			0.09***
	(18.415)			(0.004)	(44.443)			(0.004)
Urban	1053.88***	255.55***	281.92***	0.19***	2932.68***	738.98***	821.22***	0.34***
	(93.767)	(22.056)	(23.475)	(0.017)	(226.296)	(58.757)	(63.624)	(0.021)
Constant	475.40***	705.04***	906.05***	5.17***	-802.77**	590.23***	823.81***	4.12***
	(166.421)	(31.701)	(33.802)	(0.074)	(401.638)	(84.450)	(91.614)	(0.093)
Adjusted R^2	0.392	0.335	0.257	0.599	0.279	0.235	0.218	0.577
F	132.49	108.01	74.62	304.89	79.71	66.38	60.28	278.71
N	4,886	4,886	4,886	4,886	4,886	4,886	4,886	4,885

Note: 1. Standard errors in parentheses.
2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the direction of its impact on rice consumption.[23] Our results in Table 4.9 show that households' consumption of rice, both quantity and value, significantly increases with a household's agricultural landholding size. Furthermore, the impact of landholding increases with the increase in rice price (positive DiD estimate). Adjusting for inflation does not change our result significantly. Using the logarithm shows that the value of rice consumption increases more than proportionally with the increase in farming capacity.

Turning towards other food and non-food consumption, we find that the value of both other food and non-food consumption significantly increases with a household's agricultural landholding size. The DiD estimate indicates that the impact of landholding is higher for 2010, which is due to the higher rice price (Table 4.10). All this evidence supports our hypothesis that households who are involved in rice farming benefit from the price increase.

Our entire analysis indicates that when the rice price increases buyer households do not change their rice consumption value significantly compared to autarkic households, who can produce enough rice for themselves. Buyer households also stick with low quality rice to fulfil their dietary requirement. The inelastic demand for rice however, results in a negative shock on buyer households' non-rice food expenditure. Seller households, on the other hand, consume more non-rice food and non-food items due to a higher real income caused by a higher rice price. However, their consumption value of rice does not change significantly with a higher rice price.

Our findings may have important policy implications. We find that net rice buyers, a lot of which are poor, stick to lower quality rice in response to a price increase. Our results indicate that the general agricultural subsidy of the government could be replaced by a targeted subsidy on low quality rice.[24] Such a subsidy, by lowering the burden of expenditure on rice, would allow households to spend more on other

[23]Hence, with notations we defined earlier, our present model is $Y_{it} = \alpha + \beta Y_{2010} + \gamma Landholding_i + \delta Landholding_i * Y_{2010} + \psi X_i + u_i$.

[24]Bangladesh Government currently pursues a general subsidy on agriculture (Bangladesh Government, 2006, 2011b).

Table 4.9: Effect of the 2005-10 rice price increase on rice consumption

	Household quantity of rice consumption	Per capita quantity of rice consumption	Value of household rice consumption	Value of per capita rice consumption	Inflation adjusted per capita value of rice consumption	Log value of household rice consumption
	(1)	(2)	(3)	(4)	(5)	(6)
Year2010	-3.78***	-0.80***	834.54***	179.73***	80.72***	0.54***
	(0.300)	(0.066)	(8.618)	(1.860)	(1.988)	(0.006)
PC cultivable land	2.94***	0.67***	51.74***	10.99***	15.99***	-0.01*
in acre	(0.399)	(0.087)	(11.468)	(2.481)	(2.681)	(0.007)
Year2010*PC Land	2.77***	0.90***	98.21***	38.44***	33.88***	0.04***
	(0.615)	(0.135)	(17.677)	(3.822)	(4.106)	(0.011)
Total household	-0.00		0.00***			
income	(0.000)		(0.000)			
Per capita income		0.00***		0.00***		
		(0.000)		(0.000)		
Inflation adjusted					0.00***	
PC total income					(0.000)	
Log of HH total						0.07***
income						(0.003)
Family size	12.08***		305.31***			0.18***
	(0.074)		(2.130)			(0.001)
Urban	-8.46***	-1.80***	-115.00***	-23.45***	-27.58***	-0.09***
	(0.307)	(0.067)	(8.828)	(1.909)	(2.051)	(0.006)
Constant	6.01***	13.52***	-459.86***	212.64***	311.74***	5.39***
	(0.584)	(0.094)	(16.769)	(2.679)	(2.889)	(0.028)
Adjusted R^2	0.609	0.130	0.610	0.377	0.144	0.626
F	1,346.19	135.32	1,349.15	546.31	152.59	1,443.22
N	20,695	20,695	20,695	20,695	20,695	20,695

Note: 1. Standard errors in parentheses.
2.* p <0.10, ** p <0.05, *** p <0.01.

Table 4.10: Effect of the 2005-10 rice price increase on food and total consumption

	Value of household non-rice food consumption	Value of per capita non-rice food consumption	Inflation adjusted per capita value of non-rice food consumption	Log value of household non-rice food consumption	Value of household non-food consumption	Value of per capita non-food consumption	Inflation adjusted per capita value of non-food consumption	Log value of household non-food consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year2010	1921.24***	430.75***	255.50***	0.58***	1705.45***	375.05***	168.69***	0.43***
	(31.604)	(7.359)	(7.737)	(0.007)	(74.389)	(17.878)	(19.345)	(0.009)
PC cultivable land in acre	196.78***	50.88***	80.99***	0.04***	589.23***	145.39***	229.60***	0.11***
	(42.053)	(9.817)	(10.436)	(0.009)	(98.985)	(23.849)	(26.092)	(0.011)
Year2010*PC Land	707.60***	256.86***	224.51***	0.06***	1247.30***	385.92***	289.02***	0.04***
	(64.824)	(15.122)	(15.980)	(0.014)	(152.583)	(36.737)	(39.953)	(0.017)
Total household income	0.02***				0.06***			
	(0.001)				(0.002)			
Per capita income		0.02***				0.08***		
		(0.001)				(0.002)		
Inflation adjusted PC total income			0.02***				0.07***	
			(0.001)				(0.002)	
Log of HH total income				0.29***				0.39***
				(0.004)				(0.005)
Family size	453.94***			0.10***	545.13***			0.10***
	(7.811)			(0.002)	(18.387)			(0.002)
Urban	697.96***	163.22***	177.29***	0.16***	1315.09***	308.10***	342.69***	0.21***
	(32.373)	(7.553)	(7.984)	(0.007)	(76.200)	(18.349)	(19.963)	(0.008)
Constant	-75.42	453.69***	625.98***	4.57***	-1060.37***	318.00***	496.72***	3.61***
	(61.495)	(10.601)	(11.244)	(0.036)	(144.747)	(25.753)	(28.114)	(0.042)
Adjusted R^2	0.444	0.377	0.316	0.641	0.304	0.283	0.270	0.633
F	689.43	546.41	417.00	1,539.30	377.09	356.02	333.55	1,490.76
N	20,695	20,695	20,695	20,695	20,695	20,695	20,695	20,688

Note: 1. Standard errors in parentheses.
2.* p <0.10, ** p <0.05, *** p <0.01.

types of food. The policy, by contributing to the dietary requirement of poor rice buyers, may positively affect the productivity of labour and thus the wage income of labour in the short-run. This may allow them to spend more on human capital and thus increase income further (Agénor and Neanidis, 2011). This can be particularly helpful for families with infant and young children as healthier children do better at schools in the same way healthier workers perform better in their jobs (Agénor and Moreno-Dodson, 2006). Better nutrition may also play a role in the long-run cognitive and non-cognitive development of the children (World Bank, 2012). While policies like a general agriculture/food subsidy can play a similar role, the advantage of subsidising low quality rice is that it would only attract the victims of a higher food price and would therefore provide minimal pressure on the government budget.[25]

4.7 Conclusion

As long as the impact on production is limited, households who are self-sufficient in their rice consumption would not be affected much by a higher rice price. However, net rice buyer households and net rice seller households would be affected by a higher rice price through an impact on their real income. Taking advantage of a natural experiment setting by using the 2005 and 2010 waves of a household level survey from Bangladesh, we investigate the impact of a higher rice price between 2005 and 2010 on the consumption of net rice buyer households. We also investigate the impact of the same event on the consumption of net rice seller households.

Our empirical analysis finds that the increase in the rice price between 2005 and 2010 does not have any significant impact on the value of rice consumption of buyer households. Interestingly, we find a significantly negative effect of the higher rice price on the value of other food consumption of net rice buyer households. The increase in net real income caused by the higher rice price between 2005 and 2010,

[25]Such policy is even better as it would also lower the deadweight loss associated with tax as well as the administrative cost of implementing the subsidy.

on the other hand, contributes to increasing the value of other food and non-food consumption for seller households. However, such an event does not significantly affect the value of rice consumption of sellers. The insensitive consumption of rice for both buyers and sellers indicates a quadratic Engel curve for rice, in line with some earlier studies, which find a quadratic food Engel curve for developing countries.

Our findings may provide a valuable input to food policy, which aims to protect the poor from food price shocks. It indicates that an initiative by the government to provide a subsidy on low quality rice during a food price shock may protect the poor from inadequate consumption of food. This is because a significant proportion of the poor are net rice buyers and their coping mechanism allows them to stick to a low-quality and relatively low-priced rice. By relaxing their expenditure burden on rice, such a subsidy would allow poor buyers to maintain their spending on non-rice food items. Such a policy may increase labour productivity and labour wage income in the short-run and improve their socioeconomic status in the long-run. For families with infants and young children this can be very useful because food and nutrition is a valuable input for the health and cognitive development of children. The recommended policy has the potential to put a lower burden on government finances than a general food subsidy.

4.7 Conclusions

[illegible] household level [illegible] higher rice price between [illegible] on the consumption of net rice buyer households. We also investigate [illegible] the same event on the consumption of net rice seller households.

[illegible] analysis finds that the increase in the rice price between 2005 and [illegible] significant impact on the value of rice consumption of buyer households. [illegible] we find a significantly negative effect of the higher rice price [illegible] of other food consumption of net rice buyer households. The [illegible] caused by the higher rice price between 2005 and 2010.

[illegible]

Chapter 5

Conclusion

5.1 Main findings

Our analysis, using household survey data from Bangladesh, has generated several consistent findings. We find a quadratic food Engel curve, a disproportionate effect of a high rice price on the welfare of low-income households and no significant effect of the rice price increase between 2005 and 2010 on rice consumption of households who buy or sell rice. An insensitive consumption of rice for both buyers and sellers also indicates a quadratic Engel curve for rice, which is in line with our earlier findings for food. Our analysis focuses on the vulnerability of low-income households in Bangladesh, resulting from an income or a food price shock. Policy recommendations include income support and a subsidy on low-quality rice. Details of our conclusions are summarised below for each research topic.

5.2 Engel curves and equivalence scales for Bangladesh

In Chapter 2, we attempt to identify the shape of Engel curves for major expenditure categories in Bangladesh. In particular, we investigate the shape of the food Engel curve for Bangladesh using a semi-parametric model, which also takes care of the restrictions imposed by consumer theory on its functional form. Tests with the semi-parametric and parametric specifications, which simultaneously control for endogeneity, indicate a quadratic food Engel curve for Bangladesh. It thus provides additional evidence for the argument of the quadratic food Engel curve for developing countries. Our analysis, by identifying the appropriate specification of Engel curves, may contribute to improving the design of public policies with a particular focus on food security.

5.3 The impact of a large rice price increase on welfare and poverty in Bangladesh

Chapter 3 simulates the effect of a sharp rice price increase on welfare and poverty in Bangladesh. We find that using household expenditure and including behavioural responses to a price change improves the estimates of welfare loss resulting from a higher rice price. Using a semiparametric framework which also controls for endogeneity, we find a quadratic relationship between welfare change and permanent household income. Based on our results we recommend a progressive income support for the poor when food prices rise. We also find that changes in the head-count ratio due to a higher rice price depends on the choice of the poverty line. This indicates that the success or failure of public interventions may be misjudged if we use a specific poverty line.

5.4 The impact of the 2005-10 rice price increase on rice consumption in Bangladesh

In Chapter 4, we analyse the effect of a price increase between 2005 and 2010 on rice consumption in Bangladesh. In particular, we investigate the impact of that particular event on consumption of net rice buyer and net rice seller households. Our empirical analysis suggests that the increase in rice price between 2005 and 2010 does not have a significant effect on rice or total consumption of buyer households, but have a significant negative impact on the consumption of other food items. On the other hand, the same event increases the consumption of other food and non-food for seller households but does not significantly affect the consumption of rice. Our analysis supports a government subsidy on low quality rice during a food price shock, rather than a general food subsidy, aiming to protect the poor from inadequate food consumption. The recommended policy has the potential to place a lower burden on government finances than a general food subsidy.

5.5 Future work

Our motivation for some future work originates from the limitations of our research. The most obvious shortcoming of our analysis is the focus on a single data source from one particular country, Bangladesh. A generalisation of conclusions, however, requires the findings to be consistent for others countries. Therefore, an investigation into the same research question with cross-country data is on our future research agenda, even though comparability issues in such data are challenging. In addition, we ignore the effect of the food price change on household labour income in our models. Our future work will attempt to include labour market repercussions in the analysis.

5.3 The impact of a large rice price increase on welfare and poverty in Bangladesh

5.4 The impact of the 2005-10 rice price increase on rice consumption in Bangladesh

In Chapter 4, we analyze the effect of a price increase between 2005 and 2010 on rice consumption in Bangladesh. In particular, we investigate the impact of that particular event on consumption of net rice buyer and net rice seller households. Our empirical analysis suggests that the increase in rice price between 2005 and 2010 does not have a significant effect on rice or total consumption of buyer households, but have a significant negative impact on the consumption of other food items. On the other hand, the same event increases the consumption of other food and non-food for seller households but does not significantly affect the consumption of rice. Our anal-

Bibliography

AGÉNOR, P.-R. AND MORENO-DODSON, B., 2006. Public infrastructure and growth: new channels and policy implications. Policy Research Working Paper Series 4064, The World Bank. (cited on pages 1 and 92)

AGÉNOR, P.-R. AND NEANIDIS, K. C., 2011. The allocation of public expenditure and economic growth. *The Manchester School*, 79, 4 (2011), 899–931. (cited on pages 1 and 92)

AHMED, A. U. AND SHAMS, Y., 1994. Demand elasticities in rural Bangladesh: an application of the AIDS model. *The Bangladesh Development Studies*, 22, 1 (1994), 1–25. (cited on page 68)

AKSOY, M. A.; BEVERINOTTI, J.; COVARRUBIAS, K.; AND ZEZZA, A., 2010. Household income structures in low-income countries. In *Food Prices and Rural Poverty* (Eds. M. A. AKSOY AND B. HOEKMAN), chap. 4, 89–112. CEPR, The World Bank. (cited on page 70)

ALEM, Y. AND SÖDERBOM, M., 2010. Household-level consumption in urban Ethiopia: the impact of food price inflation and idiosyncratic shocks. Technical report, University of Oxford, Department of Economics. (cited on pages 3 and 68)

BANGLADESH GOVERNMENT, 2006. Food policy. Policy document, Ministry of Food and Disaster Management, Government of the People's Republic of Bangladesh. (cited on page 89)

BANGLADESH GOVERNMENT, 2007. Report of the household income and expenditure survey 2005. Report, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on pages 6 and 73)

Bangladesh Government, 2011a. Preliminary report on household income and expenditure survey - 2010. Report, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on page 37)

Bangladesh Government, 2011b. Sixth five year plan, FY2011-FY2015. Plan document, General Economics Division (GED), Planning Commission, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on page 89)

Bangladesh Government, 2011c. Statistical yearbook of Bangladesh, 2010. Report, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on page 70)

Bangladesh Government, 2011d. Yearbook of agricultural statistics of Bangladesh, 2011. Report, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on page 70)

Bangladesh Government, 2012a. Bangladesh economic review. Technical report, Finance Division, Ministry of Finance, Government of the People's Republic of Bangladesh. (cited on pages 6 and 34)

Bangladesh Government, 2012b. Report of the household income and expenditure survey - 2010. Report, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh. (cited on pages 6, 10, 34, 37, 68, and 73)

Banks, J.; Blundell, R.; and Lewbel, A., 1997. Quadratic Engel curves and consumer demand. *The Review of Economics and Statistics*, 79, 4 (1997), pp. 527–539. (cited on pages 2, 6, 7, 12, 23, and 25)

Bhalotra, S. and Attfield, C., 1998. Intrahousehold resource allocation in rural Pakistan: a semiparametric analysis. *Journal of Applied Econometrics*, 13, 5 (1998), pp. 463–480. (cited on pages 2, 7, 8, 12, 23, 26, 38, and 87)

BIERENS, H. AND POTT-BUTER, H., 1990. Specification of household Engel curves by nonparametric regression. *Econometric Reviews*, 9, 2 (1990), 123–184. (cited on pages 2 and 7)

BLACKORBY, C. AND DONALDSON, D., 1993. Adult-equivalence scales and the economic implementation of interpersonal comparisons of well-being. *Social Choice and Welfare*, 10, 2 (1993), 335–361. 10.1007/BF00182510. (cited on pages 15 and 16)

BLUNDELL, R.; CHEN, X.; AND KRISTENSEN, D., 2007. Semi-nonparametric IV estimation of shape-invariant Engel curves. *Econometrica*, 75, 6 (2007), pp. 1613–1669. (cited on pages 14 and 23)

BLUNDELL, R. AND DUNCAN, A., 1998. Kernel regression in empirical microeconomics. *The Journal of Human Resources*, 33, 1 (1998), pp. 62–87. (cited on page 12)

BLUNDELL, R.; DUNCAN, A.; AND PENDAKUR, K., 1998. Semiparametric estimation and consumer demand. *Journal of Applied Econometrics*, 13, 5 (1998), 435–461. (cited on pages 2, 6, 7, 9, 14, and 23)

BREUNIG, R. V. AND COBB-CLARK, D., 2005. Understanding the factors associated with financial stress in Australian households. *Australian Social Policy 2005*, (2005). (cited on page 9)

BREUNIG, R. V. AND MCKIBBIN, R. J., 2012. Income pooling between Australian young adults and their parents. *LABOUR*, 26, 2 (2012), 235–265. (cited on pages 12, 30, and 63)

BRINKMAN, H.-J.; DE PEE, S.; SANOGO, I.; SUBRAN, L.; AND BLOEM, M. W., 2010. High food prices and the global financial crisis have reduced access to nutritious food and worsened nutritional status and health. *The Journal of nutrition*, 140, 1 (2010), 153S–161S. (cited on pages 3 and 68)

CAMERON, A. C. AND TRIVEDI, P. K., 2005. *Microeconometrics: Methods and Applications.*

Cambridge University Press, New York, USA, 1st edn. ISBN 0521848059. (cited on pages 10 and 46)

Chen, W.-H. and Duclos, J.-Y., 2011. Testing for poverty dominance: an application to Canada. *Canadian Journal of Economics/Revue canadienne d'Ãl'conomique*, 44, 3 (2011), 781–803. (cited on pages 35 and 64)

Compton, J.; Wiggins, S.; and Keats, S., 2010. Impact of the global food crisis on the poor: what is the evidence. *London, ODI*, 99 (2010). (cited on page 68)

Dawson, P. J. and Dey, P. K., 2002. Testing for the law of one price: rice market integration in Bangladesh. *Journal of International Development*, 14, 4 (2002), 473–484. (cited on pages 44 and 73)

Deaton, A., 1989. Rice prices and income distribution in Thailand: a non-parametric analysis. *Economic Journal*, 99, 395 (Supplemen 1989), 1–37. (cited on pages 3, 34, and 43)

Deaton, A., 1997. *The analysis of household surveys: a microeconometric approach to development policy*. World Bank Publications, Washington D.C, USA, 1st edn. ISBN 0801852544. (cited on pages 38, 39, 48, and 74)

Deaton, A. and Muellbauer, J., 1980. *Economics and Consumer Behaviour*. Cambridge University Press, Cambridge, USA, 1st edn. ISBN 0521296765. (cited on pages 2 and 6)

Dorosh, P. A. and Shahabuddin, Q., 2002. Rice price stabilization in Bangladesh. Report, International Food Policy Research Institute, Washington D.C. (cited on page 34)

Engel, J. and Kneip, A., 1996. Recent approaches to estimating Engel curves. *Journal of Economics*, 63, 2 (1996), 187–212. (cited on page 12)

Fields, G., 2002. *Distribution and Development: A New Look at the Developing World*. MIT Press. ISBN 9780262561532. (cited on page 52)

FOSTER, J.; GREER, J.; AND THORBECKE, E., 1984. A class of decomposable poverty measures. *Econometrica*, 52, 3 (1984), 761–766. (cited on page 52)

FOSTER, J. E. AND SHORROCKS, A. F., 1988a. Poverty orderings. *Econometrica: Journal of the Econometric Society*, (1988), 173–177. (cited on page 52)

FOSTER, J. E. AND SHORROCKS, A. F., 1988b. Poverty orderings and welfare dominance. *Social choice and welfare*, 5, 2 (1988), 179–198. (cited on page 52)

FRIEDMAN, M., 1957. *A Theory of the Consumption Function*. Princeton University Press. (cited on page 45)

GOLETTI, F.; AHMED, R.; AND CHOWDHURY, N., 1991. *Optimal stock for the public foodgrain distribution system in Bangladesh*. International Food Policy Research Institute. (cited on page 68)

GOZALO, P. L., 1997. Nonparametric bootstrap analysis with applications to demographic effects in demand functions. *Journal of Econometrics*, 81, 2 (1997), 357 - 393. (cited on page 9)

GRIGG, D., 1994. Food expenditure and economic development. *GeoJournal*, 33, 4 (1994), 377–382. 10.1007/BF00806419. (cited on page 8)

HARDLE, W. AND MAMMEN, E., 1993. Comparing nonparametric versus parametric regression fits. *The Annals of Statistics*, 21, 4 (1993), pp. 1926–1947. (cited on pages 15, 21, 48, and 51)

HARDLE, W. AND MARRON, J. S., 1985. Optimal bandwidth selection in nonparametric regression function estimation. *The Annals of Statistics*, 13, 4 (1985), pp. 1465–1481. (cited on page 46)

HASAN, S. A., 2012. Engel curves and equivalence scales for Bangladesh. *ASARC Working Paper Series, Australian National University*, , 15 (2012). (cited on pages 46 and 87)

HASAN, S. A., 2013. The impact of a large rice price increase on welfare and poverty in Bangladesh. *ASARC Working Paper Series, Australian National University*, , 11 (2013). (cited on page 68)

HEADEY, D. AND FAN, S., 2008. Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural Economics*, 39 (2008), 375–391. (cited on page 68)

IVANIC, M. AND MARTIN, W., 2008. Implications of higher global food prices for poverty in low-income countries. *Agricultural Economics*, 39 (2008), 405–416. (cited on pages 2, 3, 34, and 68)

KHANDKER, S. R., 2009. Poverty and income seasonality in Bangladesh. *World Bank Policy Research Working Paper Series*, 4923 (2009), 1–54. (cited on page 7)

KHANDKER, S. R.; KOOLWAL, G. B.; AND SAMAD, H. A., 2010. *Handbook on Impact Evaluation: Quantitative Methods and Practices*. World Bank Publications, Washington D.C, USA, 1st edn. ISBN 0821380284. (cited on page 82)

KNIGHT, C. A. AND ACKERLY, D. D., 2002. Variation in nuclear DNA content across environmental gradients: a quantile regression analysis. *Ecology Letters*, 5, 1 (2002), 66–76. (cited on page 18)

KOENKER, R. AND HALLOCK, K. F., 2001. Quantile regression. *The Journal of Economic Perspectives*, 15, 4 (2001), pp. 143–156. (cited on page 18)

LIVIATAN, N., 1961. Errors in variables and Engel curve analysis. *Econometrica*, 29, 3 (1961), pp. 336–362. (cited on page 14)

MAS-COLELL, A.; WHINSTON, M.; AND GREEN, J., 1995. *Microeconomic Theory*. Oxford student edition. Oxford University Press. ISBN 9780195073409. (cited on page 39)

MEYER, B. D. AND SULLIVAN, J. X., 2012. Consumption and income poverty in the United States. In *The Oxford Handbook of the Economics of Poverty* (Ed. P. N. JEFFERSON), 49–74. Oxford University Press, New York. (cited on pages 35 and 45)

MGHENYI, E.; MYERS, R. J.; AND JAYNE, T., 2011. The effects of a large discrete maize price increase on the distribution of household welfare and poverty in rural Kenya1. *Agricultural Economics*, 42, 3 (2011), 343–356. (cited on pages 3, 35, 39, 41, 43, 44, 45, 46, and 61)

MYERS, R. J., 2006. On the costs of food price fluctuations in low-income countries. *Food Policy*, 31, 4 (2006), 288 – 301. (cited on pages 3, 35, and 62)

NAIK, N. Y. AND MOORE, M. J., 1996. Habit formation and intertemporal substitution in individual food consumption. *The Review of Economics and Statistics*, 78, 2 (May 1996), 321–28. (cited on page 80)

NEWEY, W. K.; POWELL, J. L.; AND VELLA, F., 1999. Nonparametric estimation of triangular simultaneous equations models. *Econometrica*, 67, 3 (1999), pp. 565–603. (cited on pages 14 and 45)

PENDAKUR, K., 1999. Semiparametric estimates and tests of base-independent equivalence scales. *Journal of Econometrics*, 88, 1 (1999), 1 – 40. (cited on pages 9, 14, and 16)

RAVALLION, M., 1990. Rural welfare effects of food price changes under induced wage responses: theory and evidence for Bangladesh. *Oxford Economic Papers*, 42, 3 (1990), pp. 574–585. (cited on pages 3 and 34)

RAVALLION, M., 1992. Poverty comparisons. *Living Standards Measurement Study*, , 88 (1992). (cited on pages 35, 64, and 65)

RAVALLION, M. AND SEN, B., 1996. When method matters: monitoring poverty in Bangladesh. *Economic Development and Cultural Change*, 44, 4 (1996), pp. 761–792. (cited on page 70)

ROBINSON, P. M., 1988. Root-n-consistent semiparametric regression. *Econometrica*, 56, 4 (1988), pp. 931–954. (cited on pages 30 and 63)

ROSENZWEIG, M., 2001. Savings behaviour in low-income countries. *Oxford Review of Economic Policy*, 17, 1 (2001), 40–54. (cited on page 39)

SUMMERS, R., 1957. A note on least squares bias in household expenditure analysis. Cowles Foundation Discussion Papers 29, Cowles Foundation for Research in Economics, Yale University. (cited on page 14)

UNITED NATIONS, 2013. The state of food insecurity in the world. Technical report, Food and Agriculture Organization, United Nations. (cited on page 1)

VERARDI, V. AND DEBARSY, N., 2011. Robinson's squareroot-of-n-consistent semiparametric regression estimator in stata. Working Papers 1110, University of Namur, Department of Economics. (cited on page 19)

WOOLDRIDGE, J. M., 2010. *Econometric Analysis of Cross Section and Panel Data*, vol. 1 of *MIT Press Books*. The MIT Press. (cited on page 25)

WORKING, H., 1943. Statistical laws of family expenditure. *Journal of the American Statistical Association*, 38, 221 (1943), pp. 43–56. (cited on page 8)

WORLD BANK, 2010. Food price increases in south asia: national responses and regional dimensions. Mssd discussion paper no. 46, The Worldbank, Washington D.C. (cited on pages 2, 34, 42, and 69)

WORLD BANK, 2012. Food prices, nutrition, and the millennium development goals. Global monitoring report 2012, The Worldbank, Washington D.C. (cited on pages 1, 68, and 92)

YATCHEW, A., 1998. Nonparametric regression techniques in economics. *Journal of Economic Literature*, 36, 2 (1998), pp. 669–721. (cited on pages 13 and 46)

YATCHEW, A., 2003. *Semiparametric Regression for the Applied Econometrician*. No. 9780521812832 in Cambridge Books. Cambridge University Press. (cited on pages 13 and 46)

Yatchew, A.; Sun, Y.; and Deri, C., 2000. Efficient estimation of semiparametric equivalence scales with evidence from South Africa. *working paper, University of Toronto, Dept. of Economics*, (2000). (cited on page 11)

Yatchew, A.; Sun, Y.; and Deri, C., 2003. Efficient estimation of semiparametric equivalence scales with evidence from South Africa. *Journal of Business & Economic Statistics*, 21, 2 (2003), 247–257. (cited on pages 9 and 15)